DEVELOPING A PROCEDURE TO IDENTIFY PARAMETERS FOR CALIBRATION OF A VISSIM MODEL

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DEVELOPING A PROCEDURE TO IDENTIFY PARAMETERS FOR CALIBRATION OF A VISSIM MODEL

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SUMMARY

The calibration of microscopic traffic simulation models is an area of intense study; however, additional research is needed into how to select which parameters to calibrate. In this project a procedure was designed to eliminate the parameters unnecessary for calibration and select those which should be examined for a VISSIM model.

The proposed iterative procedure consists of four phases: initial parameter selection, measures of effectiveness selection, Monte Carlo experiment, and sensitivity analysis and parameter elimination. The goal of the procedure is to experimentally determine which parameters have an effect on the selected measures of effectiveness and which do not. This is accomplished through the use of randomly generated parameter sets and subsequent analysis of the generated results.

The second phase of the project involves a case study on implementing the proposed procedure on an existing VISSIM model of Cobb Parkway in Atlanta, Georgia. Each phase of the procedure is described in detail and justifications for each parameter selection or elimination are explained. For the case study the model is considered under both full traffic volumes and a reduced volume set representative of uncongested conditions. The case study shows that the procedure is effective and that many parameters can be eliminated from consideration before model calibration is attempted.

CHAPTER 1

INTRODUCTION

In the last few decades traffic simulation has grown into a major resource for transportation engineers. The ability to simulate a proposed project prior to implementation and evaluate the potential benefits and costs allows for significant optimization of potential projects and improvements. This of course assumes that the simulation accurately, or at least reasonably, reflects reality.

In order for a traffic simulation to accurately describe reality it must utilize a valid model and be properly calibrated. A valid model implies that the underlying simulation logic reasonably reflects real-world operations. A calibrated simulation means that the input parameters provided by the user (e.g. driver aggressiveness or desired speed) allow the simulation program's valid model to recreate the specific network under consideration. Model calibration is a frequent area of study by transportation engineers and there are a number of proposed procedures for calibrating different simulations, such as linear regression or genetic algorithms. These methods are used in order to determine input parameters values that produce simulation results representative of field data.

1.1 Study Need

One area of model calibration in which meaningful contributions are still needed is the selection of parameters for calibration. Most calibration procedures assume only a small set of the available simulation parameters are to be included in the calibration process. However, there is usually no formal procedure for selecting these parameters other than selecting the parameters which appear to the user as most likely to have a significant effect on the simulation. An incomplete set of selected parameters for calibration may lead to issues rendering the simulation imprecise or the calibration method producing unrealistic parameters values.

1.2 Study Objective

The purpose of this project is to create and test a procedure to determine which parameters should be considered for calibration in a typical transportation simulation package. The developed procedure is demonstrated on an arterial simulation utilizing the simulation program PTV VISSIM. It is anticipated that this procedure could be followed to select calibration parameter sets for other facility types (e.g. freeways, toll plaza) and simulation platforms. Final calibration of the model is not an objective of this study.

1.3 Study Overview

This study focuses on two main objectives: proposing a procedure for determining parameters for calibration and a case study to demonstrate how the procedure works in practice. A summary of each section of the report is included below.

1.3.1 Background

The second chapter discusses the inner workings of VISSIM, the simulation program used for this study. Included in the chapter are sections on the physical representation of networks with links and connectors, how driving behavior is modeled with respect to car following and lane changing, model calibration, output files and the formats available, and how input files or ".inp files" are created and read by the program.

1.3.2 Literature Review

The literature review chapter is divided into two sections. The first section is an overview of relevant previous studies. These studies are primarily related to simulation calibration for freeway and urban signalized arterial models. Many of the cited studies utilize the genetic algorithm for calibration. The second section delves into the need for a procedure to determine which parameters should be included in a model's calibration.

1.3.3 General Procedure

The procedure proposed in this study is outlined and explained in this chapter. There is a section in the chapter for each of the four steps of the procedure:

1. Initial Parameter Selection
2. Measures of Effectiveness Selection
3. Monte Carlo Experiment
4. Sensitivity Analysis and Parameter Elimination

There is also a final section explaining the iterative aspect of the procedure and stopping criteria.

1.3.4 Case Study: Cobb Parkway Model

The case study presented in this chapter illustrates the proposed procedure on a 13 intersection model of Cobb Parkway in Atlanta, GA. Two scenarios are considered, one utilizing 100% of the existing AM traffic and a second with AM traffic reduced uniformly by 25% to create an uncongested scenario. The two scenarios provided similar results and show that there are between 5-10 important parameters that should be included in calibration. The parameter sets chosen are almost identical between the two scenarios.

CHAPTER 2

BACKGROUND

2.1 VISSIM Overview

"VISSIM is a discrete, stochastic, time step based microscopic traffic flow simulation model" [13]. VISSIM 4.30 was used for this study. The model uses two different modules to produce the output: a traffic simulator and a signal state generator. The signal state generator determines the signal status at each time step and returns the value to the traffic simulator as shown in Figure 1. The traffic simulator in VISSIM allows drivers to react to vehicles ahead of them as well as vehicles to either side of the driver. Drivers are also given a higher measure of alertness as they get nearer to a traffic signal [13].

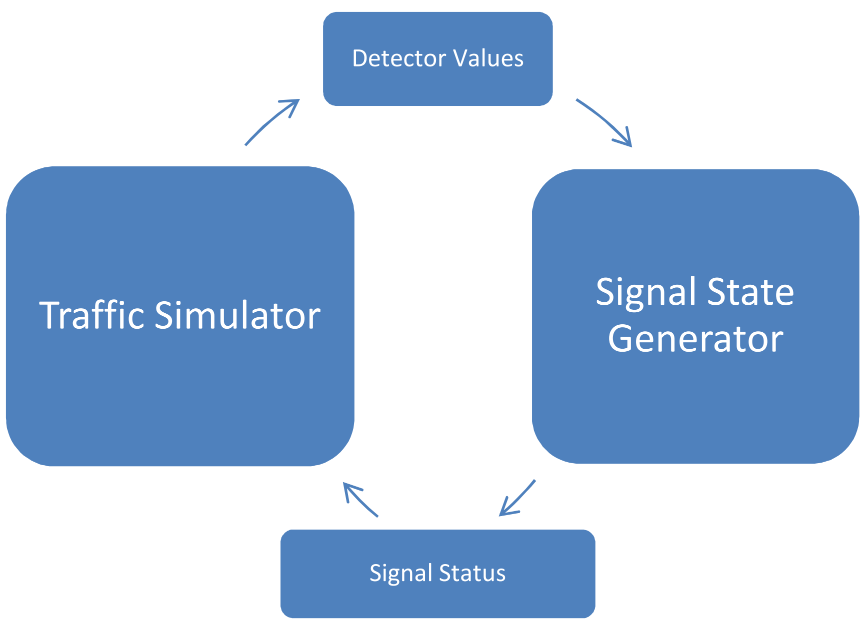


Figure 1: VISSIM Modules [13]

The traffic flow model used by the traffic simulator relies on one of the following models: the "Wiedemann 74" car following model or the "Wiedemann 99" car following model. The Wiedemann 74 car following model is a psycho-physical driver behavior model developed by Wiedemann at the Technical University of Karlsruhe, Germany in 1974 [16]. The basic premise of the model is that a driver will continue at a constant speed until he perceives a vehicle in front of him to be traveling either faster or slower than his current speed. Then the driver will accelerate or decelerate accordingly. Due to the driver's imperfect perception he will overcompensate and go through an iterative process of acceleration and deceleration until a following equilibrium is reached. Stochastic distributions of speed and spacing thresholds account for differences between drivers [16]. The parameters that determine how these thresholds are calculated will be discussed later. The Wiedemann 99 car following model is primarily suited for freeway conditions [13]. A discussion of the Weidemann 99 car following model is not included with this review as this study is centered on arterial operations.

2.2 Network Representation

Networks in VISSIM are represented through a series of links and connectors. Generally, when a model is created these links and connectors are laid over a satellite image of the network being modeled. Links can be single or multi-lane roadway segments with traffic flow in only one direction. Vehicles can only travel from one link to the next over a connector. Overlapping links have no interaction with each other. Each link is defined by its name, location, length, lane width, number of lanes, link type and gradient. The link type determines if the link is an urban roadway, freeway, pedestrian path, or any custom user defined link type. The link type contains information on what types of vehicles are allowed onto the link and the driving behavior on the link. The different driving behavior sets are defined by the user and are explained in detail in section 2.3.

A connector connects two links and is defined by the following attributes: name, which links it connects, which lanes connect to each other, gradient, lane closure, emergency stop distance, lane change distance, and desired direction. The lane closure is used if certain vehicle types are not allowed on the connector. The emergency stop distance defines at what point before the connector a vehicle attempting to get onto the connector will stop and wait until it can change lanes. The lane change distance defines at what distance before the connector a vehicles attempting to get onto the connector will start to try and change lanes. The desired direction attribute is only used if vehicles are not traveling on routes defined by the user.

Vehicles are placed onto the network through an input at the beginning of a link. Usually these inputs are at all of the edges of the network. The inputs are defined by the number of vehicles per hour that they create as well as the vehicle composition (i.e. 80% cars, 20% trucks). The vehicle composition also determines the vehicles' desired speed distribution. The desired speed distribution defines the range of speeds the drivers of this vehicle composition will try to travel when not hindered by another vehicle. If a driver cannot reach his desired speed because of another vehicle he will look for an opportunity to pass the vehicle. This parameter can affect how vehicle platoons operate on the network.

A vehicle's route is determined by static routing decisions. When a vehicle crosses a routing decision it is assigned one of the predetermined routes for that routing decision based on user selected probabilities. If a vehicle crosses another routing decision before the end of their previous route then that routing decision is ignored. If a vehicles cannot find the next link on its route then that vehicle is removed from the network.

2.3 Driving Behavior

A vehicle's behavior in VISSIM is controlled by its vehicle type and the driving behavior parameter set assigned to the link that the vehicle is on. The vehicle type determines the mechanical characteristics of the vehicle such as width, length, maximum acceleration and deceleration, and desired acceleration and deceleration. The driving behavior parameter set contains many parameters that control four types of behavior: following behavior, lane change behavior, lateral behavior, and signal control behavior. For a small network there is usually only one driving behavior parameter utilized for the entire network.

2.3.1 Following Behavior

The car following parameters include the choice of car following model (e.g. Wiedemann 74 or Wiedemann 99), the parameters required for the chosen car following model, the look ahead distances, and temporary lack of attention parameters. The parameters needed for the Wiedemann 74 car following model are the average standstill distance (ax), additive part of safety distance (bx_{add}), and multiplicative part of safety distance (bx_{mult}). The average standstill distance defines the average desired distance between stopped cars and has a fixed variation of ±3.28ft [13]. The additive part of safety distance and multiplicative part of safety distance determine the desired safety distance between two moving vehicles using the formula [13]:

$$Safety\ Distance = ax + bx$$

Where $bx = (bx_{add} + \ bx_{mult} * z)\sqrt{v}$

$$z = \ N(0.5, 0.15) between\ [0,1]$$

$$v = vehicle\ speed$$

This formula shows that for larger values of bx_{add} and bx_{mult} the safety distance also becomes larger and vice versa. The variable bx_{add} will also always have a greater or equal affect on the safety distance than bx_{mult} because of the normally distributed random variable z. This formula is used by the model to calculate the desired safety distance between vehicles at every time step of the simulation and modify the vehicles acceleration, deceleration, and desire to pass accordingly.

There are three parameters that define the distance a driver will look ahead and the distance from other vehicles and traffic control devices at which a driver will begin to react. The first parameter, the maximum look ahead distance, determines the furthest distance that a driver may see ahead. The second parameter, the number of observed vehicles, defines how many vehicles ahead a driver may consider. The actual look ahead distance a driver uses in the minimum of the maximum look ahead distance and the distance required for the driver to see the number of observed vehicles. The number of observed vehicles should be set to at least two vehicles or under certain conditions drivers will not look ahead far enough to see traffic signals and the signals will be ignored [13]. The third parameter, the minimum look ahead distance, is only used if vehicles (e.g. bicycles) are allowed to queue next to each other in a lane. In this situation drivers are forced to look past their number of observed vehicles to the minimum look ahead distance. If there is no lateral behavior present this parameter can be set to zero.

The temporary lack of attention parameters attempt to mimic reality by allowing drivers to delay their response time to a preceding vehicle or traffic signal. This behavior is defined by the length of time of the lack of attention and the probability of this behavior to occur. It is common for this type of behavior to be excluded from models and it is excluded from this study.

2.3.2 Lane Change Behavior

Lane changes in VISSIM models are made for two reasons: necessary lane changes to follow a route and free lane changes in order to reach the driver's desired speed. All lane changes are governed by the gap defined by the time headway between the lane changing vehicle and the trailing vehicle in the lane the lane changing vehicle wishes to enter. Necessary lane changes can be made more aggressive by manipulating vehicle specific parameters that affect the aggressiveness of the lane changing vehicle driver and the trailing vehicle driver. These parameters are maximum deceleration, reduction rate, and accepted deceleration. The drivers will first decelerate at their accepted deceleration rates, but if the lane changing vehicle driver cannot change lanes within a certain distance of the emergency stop position the drivers will decelerate an additional 1ft/s^2 until they reach their maximum deceleration value at the emergency stop position [13]. At this position the lane changing vehicle will stop and wait, potentially blocking its current lane, to make a lane change. An example of how these parameters affect the vehicles' deceleration is shown in Figure 2. If the lane changing vehicle's driver is not able to change lanes the vehicle will eventually be deleted from the network and recorded as an error. The length of time to wait before being deleted is the waiting time before diffusion parameter.

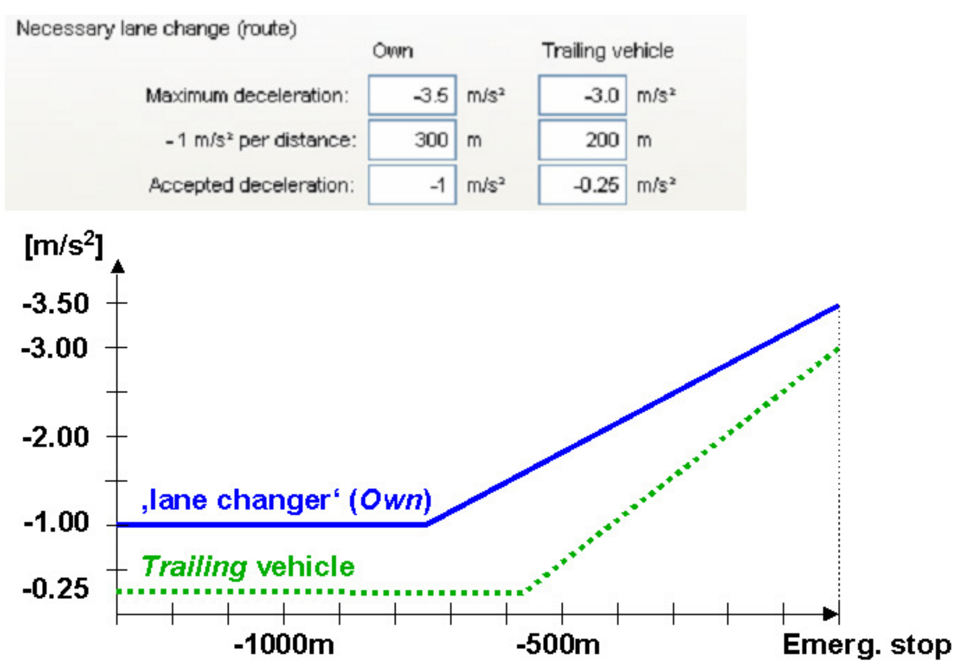


Figure 2: Necessary Lane Change Parameters [13]

Additional parameters affecting all lane changes include the selection of general behavior, minimum headway front/rear, safety distance reduction factor, and maximum deceleration for cooperative braking. The general behavior selection establishes if vehicles are only allowed to pass on the left or if they may pass in any lane. For an urban, signalized network free lane selection is the appropriate behavior. The minimum headway front/rear determines the minimum distance needed to change lanes at a standstill. The safety distance reduction factor reduces the safety distance determined by the car following model for both the lane changing vehicle and the trailing vehicle until the lane change is completed. The value for maximum deceleration for cooperative braking is the largest amount of deceleration that a trailing vehicle will take in order to allow a lane changing vehicle into its lane. There is no way to modify the aggressiveness of free lane changes directly. To make free lane changes more aggressive changes must be made to the safety distance from the car following model [13].

2.3.3 Lateral Behavior

Lateral behavior parameters are used to control the interactions of vehicles traveling next to one another in the same lane such as bicycles. If there is no lateral behavior present than these parameters can be neglected

2.3.4 Signal Control Behavior

When approaching a signal there are two new sets of behavior that are applied to the vehicle: reaction to an amber signal and reduction in safety distance close to the stop bar. A driver's reaction to an amber signal can be based on either a continuous check or one decision model. In the continuous check model the driver's assume that the light stays amber for two seconds and evaluate their decision to continue or stop at each time step of the simulation until they cross the signal. In the one decision model three probability factors, α, β_1, and β_2, are used to determine the probability that the driver will stop at an amber light. The formula used to calculate the probability of stopping is:

$$p = \frac{1}{1 + e^{-\alpha - \beta_1 v - \beta_2 dx}}$$

where *v* is the current velocity and *dx* is the distance to the signal [13]. For this study the continuous check model is used exclusively. Three parameters define the reduction in safety distance close to a stop bar: the reduction factor and the distances upstream and downstream of the stop bar to apply the reduction factor. Whenever a vehicle is within those distances from a stop bar the safety distance from the car following model will be multiplied by the reduction factor from above resulting in vehicles driving closer to each other and allowing for more aggressive lane changes.

2.4 Model Calibration

After a model is created all of the parameters discussed in the previous sections must be modified from their default values to values that will allow the model to best reflect the particular network under study. An often utilized procedure for calibration is by using a genetic algorithm to produce a set of parameters that results in a simulated set of selected measures of effectiveness similar to the values measured in the real world. This procedure will be explained in more detail in the next chapter. Selected measures of effectiveness could be travel times, flows, capacities, delay values, queue lengths, or any combination thereof.

Before the genetic algorithm is used however, the parameters to be included in the calibration must be selected. In general it is too time consuming and ineffective to attempt to calibrate all of the available parameters in the model, particularly since a number of the parameters may have a minimal effect on the model accuracy. Therefore, the list of parameters to be calibrated should be made as small as reasonably possible without eliminating potentially influential or important parameters. Table 1 shows a complete list of every available parameter along with a brief definition of each.

Table 1: Complete List of Parameters [13]

#	Parameter	Definition
Base Distributions		
1	Maximum acceleration	Max. technically feasible acceleration (only regarded on slopes)
2	Desired acceleration	Acceleration used with no other influences
3	Maximum deceleration	Max. technically feasible deceleration
4	Desired deceleration	Deceleration used with no other influences
5	Desired speed distribution	Range of desired speeds assigned to drivers on the network
Following Behavior		
6	Look ahead distance minimum	Used when a vehicle will reach the number of observed vehicles laterally and must be forced to look ahead
7	Look ahead distance maximum	Max. distance allowed for looking ahead
8	Number of observed vehicles	How many vehicles or other objects a driver can observe and react to
9	Temporary lack of attention duration	How long a driver will be distracted for
10	Temporary lack of attention probability	Probability that a given driver is distracted
11	Choice of car following model	Choice of Wiedemann 74, 99 or no interaction models
11 (Option 1)	**Wiedemann 74 Parameters**	**ax, bx_{add}, bx_{mult}**
12	Average standstill distance (ax)	Avg. desired distance between stopped cars
13	Additive part of safety distance (bx_add)	Adjustment factor for safety distance while moving
14	Multiplicative part of safety distance (bx_mult)	Adjustment factor for safety distance while moving
11 (Option 2)	**Wiedemann 99 Parameters**	**CC0-CC9**

Table 1: (continued)

15	CC0 standstill distance	Desired distance between stopped cars
16	CC1 headway time	Adjustment factor for safety distance while moving
17	CC2 ‘following’ variation	Determines the amount of oscillation of vehicles while following each other
18	CC3 threshold for entering ‘following’	Determines when a vehicle reacts to the vehicle in front of it
19	CC4/CC5 ‘following’ thresholds	Controls speed differences during the 'following' state
20	CC6 speed dependency of oscillation	Determines the effect of distance on oscillations while following
21	CC7 oscillation acceleration	Acceleration during oscillations
22	CC8 standstill acceleration	Desired acceleration when starting from a standstill
23	CC9 acceleration at 80 km/hr	Desired acceleration at 80 km/hr
11 (Option 3)	**No Interaction Between Vehicles**	**No related parameters (used for simplified pedestrian models)**
Lane Change Behavior		
24	Free lane selection or Right side rule	Determines rules for overtaking
25	Maximum Deceleration (own)	Max. deceleration for necessary lane changes
26	Maximum Deceleration (trailing)	Max. deceleration for necessary lane changes
27	Accepted Deceleration (own)	Accepted deceleration for necessary lane changes
28	Accepted Deceleration (trailing)	Accepted deceleration for necessary lane changes
29	Reduction rate (as meters per 1 ft/s²) (own)	Reduces maximum deceleration as distance to the stop position decreases
30	Reduction rate (as meters per 1 ft/s²) (trailing)	Reduces maximum deceleration as distance to the stop position decreases
31	Waiting time before diffusion	Max. time a vehicle will wait to change lanes before it is removed from the network
32	Minimum headway (front/rear)	Min. distance to the vehicle in front that must be available for a lane change in a standstill condition

Table 1: (continued)

33	To slower lane if collision time above	Min. time headway towards the next vehicle on the slow lane so that a vehicle on the fast lane changes to the slower lane (only used if right side rule is selected)
34	Safety distance reduction factor	Adjustment factor for safety distance during lane changes
35	Maximum deceleration for cooperative braking	Max. deceleration a vehicle would use for cooperative braking allowing a vehicle to change into its own lane
Lateral Behavior		
36	Desired position at free flow	Desired lateral position, either middle, any, or right
37	Observe vehicles on next lane	Drivers observe and react to vehicles in adjacent lanes
38	Diamond shaped queuing	Allows for staggered queues used by cyclists
39	Overtake on same lane	Determines which vehicles can be overtaken within the same lane
40	Minimum lateral distance	Min. lateral distance for passing vehicles on the same lane
Signal Control Behavior		
41	Continuous check or One decision model	Choice of amber signal decision model
42	Alpha (one decision model only)	Adjustment parameter for the one decision model
43	Beta 1 (one decision model only)	Adjustment parameter for the one decision model related to the vehicle's velocity
44	Beta 2 (one decision model only)	Adjustment parameter for the one decision model related to the distance to the signal
45	Reduction factor	Adjustment factor for safety distance during lane changes near signals
46	Distance upstream of stop bar	Upstream distance from the stop bar to apply the reduction factor
47	Distance downstream of stop bar	Downstream distance from the stop bar to apply the reduction factor
Connector Parameters		
48	Emergency stop distance	Last possible position for a vehicle to change lanes
49	Lane change distance	Distance before the connector that vehicles will begin to attempt to change lanes
50	Desired direction	Used to direct vehicles without routes (unused if routes are defined)

2.5 Output Files

Before useful data can be retrieved from a simulation the model must be setup to output the desired data. There were four types of outputs used in this study: travel time, delay, queue length, and distribution of green times. For some outputs measurement devices must be placed on the network at the desired location to record the data. The details of obtaining and utilizing each output are explained below.

2.5.1 Travel Time

Travel time data is obtained by placing travel time segments onto the network. A travel time segment is defined by its start point, end point, and the type of vehicles it records data for (e.g. only trucks or all vehicles). Once travel time segments have been placed they must be configured through the evaluations toolbar in VISSIM.

Configuring a travel time segment requires specifying when the segment will start to record data, when it will stop recording data, how often it will report the data, and how it will present the final report. For most large models it is necessary to include a warm up time for the model and only start recording data after this warm up period. An alternative method is to record data for the entire simulation and ignore the results from the warm up period. This alternative method does require aggregating the data in sufficiently small intervals that allow for the identification of the warm-up period. Depending on the type of model being simulated and the type of analysis being undertaken the travel times can be aggregated over the entire simulation period or every few seconds.

The final report can be presented in either raw form or compiled form. The raw form is an ASCII, semicolon delimited, text file with each vehicle's travel time record listed in chronological order. This format negates any aggregation settings. The compiled format, also an ASCII, semicolon delimited, text file, presents the results in order of the times that the data was recorded for each travel time segment. For each recording the average travel time is reported as well as the size of the sample used in determining the average. Usually, the compiled format is easier to work with and more useful than the raw data format.

2.5.2 Delay

Delay measurements are also recorded over travel time segments; although delay measurements can be over one or multiple segments. VISSIM defines delay as the actual travel time of a vehicle minus the ideal travel time with no traffic or signalization.

Delay measurements are configured with the same options as travel time measurements: when the segment will start to record data, when it will stop recording data, how often it will report the data, and how it will present the final report. The same guidelines for warm up times and aggregation of data for travel time measurements also apply to delay measurements.

The raw data is also presented similarly to travel time data with every single recording logged chronologically in a text file. The compiled format is also similar to the travel time data version and includes additional data other than the average delay per vehicle for the segment such as the average time vehicles spent at a standstill position, the average number of stops vehicles made, the size of the vehicle sample, the average delay per person, and the number of persons included in the sample. Again the compiled data is generally more useful than the raw.

2.5.3 Queue Length

Queue length data is recorded through queue counters which can be placed on the network. Queue counters are defined by the link they are on and their position on the link. Four parameters are used to configure the definition of a queue for the simulation.

The four parameters used to define a queue are: begin velocity, end velocity, maximum headway, and maximum length. Begin velocity specifies the speed threshold at which a vehicle is considered to have entered the queue (i.e. when a vehicles speed drops below the begin velocity they are a part of the queue). The default value for begin velocity is 3.1 mph. End velocity is the speed threshold at which a vehicle is considered to have left the queue. The default value for end velocity is 6.2 mph. The maximum headway is the largest distance between two vehicles before the queue is considered disrupted. The default value is 65.6 ft. The maximum length parameter is the distance at which the queue counter will stop measuring any increases in the queue length. This parameter can be used to allow for the measurement of queues at individual intersections rather than one long queue that spills back through other intersections. The default value for this parameter is 1,640.4 ft. The first three parameters are typically used at their default value however special attention must be paid to the fourth parameter. If the maximum length is set too low the average or maximum queue lengths will be artificially reported as equal to (or near) the set maximum length parameter value instead of the actual value. The queue counters must also be configured for when to start recording data, when to stop recording data, how often to report the data. As before warm up periods may need to be observed and accounted for in any analysis.

Queue counter data is only reported in one format. That format is similar to the compiled formats of the travel time and delay measurement output files. For each time period specified the output file reports the average queue length in feet as well as the maximum queue length in feet and the average number of stops made by vehicles in the queue.

2.5.4 Distribution of Green Times

The distribution of green times can be useful information if the model utilizes actuated traffic signals. The output file for the distribution of green times requires no additional measurement devices to be placed on the network, instead recording data for every traffic signal in the model. The only parameters required to configure the output file are when to start and stop recording the data. There is no option for aggregation of data.

There is only one format to report the data and it includes various methods of displaying the results. This format is the only format that does not exclusively use the semicolon delimited format. For each signal controller there is a table displaying the average green times for each signal group, a table displaying the frequency of each green time length and red time length for each signal group, and a separate histogram for each signal group displaying the frequency of each green and red time length.

2.5.5 Error Files

If there is a single error during a simulation then VISSIM creates an error file containing the data explaining the error. There are three primary errors that may be present in a report. These errors are outlined in Table 2 below.

Table 2: Common VISSIM Simulation Errors [13]

Error Type	Explanation
1. Vehicle deleted from the network (route)	Vehicle reached the end of a link while searching for the next link of the route
2. Vehicle deleted from the network (lane change)	Vehicle waited longer than the specified waiting time before diffusion while attempting to change lanes
3. Vehicles left off of the network	Vehicle input did not generate enough vehicles because the discharge rate was smaller than the input flow

The first two error types result when the model removes a stalled vehicle (i.e. a vehicle which is unable to resolve a model conflict and move forward in its trip). The model essentially assumes that in the real world a driver would find a way to proceed and thus any blockage related to the stalled vehicle is not reflective of the likely real world conditions. Therefore, when a vehicle is stalled it is removed from the system. The third error type results when the inputs to the network are higher than the network capacity.

In large networks or networks with high traffic volumes or levels of congestion one of the first two error types will almost certainly occur. The presence of the errors may or may not be an issue that requires attention. For example, if the model has 5,000 vehicles driving on the network during the simulation period and 10 are removed due to errors then the effect is probably, although not necessarily, insignificant. If in the same example 500 vehicles are removed this is likely indicative a significant modeling issue that must be addressed by the modeler. Reviewing the error files and determining what mitigation measure should, if any, be taken is the responsibility of the modeler as VISSIM will run to completion and report measures of effectives with these errors present. The modeler must make the decision on whether the errors are significant or not for each specific case based on the modeler expertise and judgment.

The third error type is generally more serious. If actual field input values are being used then this error should not occur. If it does occur then it is clear that the model network (or at least the entry point in question) has a lower capacity than the actual network and the model is flawed. A situation where this type of error may occur and not necessarily be a result of modeling error is when all of the traffic inputs are increased uniformly. This may result in certain entry points being unable to process all of the vehicles set to enter the network due to the current signal timings or other circumstances that accurately reflect of real world conditions. Again, the significance of any errors and any required mitigation should be determined by the modeler as part of the model development and testing.

2.6 Input Files

The files used to store all of the data necessary to build a VISSIM model are called ".inp files." These files are ASCII text files that are newline delimited. On each line is either a header or an object name followed by its respective value. Every single portion of the model including links, connectors, vehicle inputs, and data measuring devices are stored in this text file. The only modeling data not included in the .inp file are the signal timing plans, unless simple pre-timed signals are used, and the list of which types of data to record and output. The signal timing plans are stored in separate files for each signal controller, and the list of which types of data to record is stored in a configuration file which can be used in conjunction with multiple .inp files. It is important to note that the configuration file only lists which types of data to record and does not include any information on the actual measurement devices on the network and their respective configuration settings. All of this information is stored in the .inp file. The text based nature of the input files makes them simple to edit without having advanced knowledge of the inner workings of VISSIM itself.

CHAPTER 3

LITERATURE REVIEW

3.1 Previous Related Studies

Microscopic traffic simulation is a rapidly developing field and many studies have been done to more clearly define the abilities and limitations of the models. The majority of studies done focus on parameter optimization as opposed to the parameter sensitivity analysis as done for this project. Many utilize a genetic algorithm in order to create the best set of input parameters so that the model produces results similar to reality. The studies that focus on VISSIM tended to be divided between those examining freeway and those examining signalized intersection operations. The freeway studies generally use the Wiedemann 99 car following parameters, and the urban studies use the Wiedemann 74 parameters. In all of the studies these parameters are considered to be important to the model's calibration and results. Both groups of studies also typically include parameters such as look-ahead distance and waiting time before diffusion in addition the car following parameters. Outlined below are many of the studies done to investigate the effects or optimization of the input parameters in VISSIM.

3.1.1 Calibration of VISSIM for Shanghai Expressway Using Genetic Algorithm (2005)

This report was completed by researchers from the Department of Traffic Engineering at Tongji University for the 2005 Winter Simulation Conference. The paper describes the methodology and results of the calibration of a model of an 8.4 km segment of the North-South Shanghai Expressway. Field data from the Traffic Information Collecting System in Shanghai was used as the basis for the calibration [17].

The data used for the calibration was collected via loop detectors, video cameras, and manual traffic counts at entrance and exit ramps. The data included volume, speed, vehicle type, occupancy, headway, and origin destination tables for the entrance and exit ramps in each direction [17].

The parameters for calibration were selected "according to the characteristics of expressway traffic flow and practical experiences." The selected parameters for calibration were:

1. Desired lane change distance (DLCD)
2. Waiting time before diffusion (WTBD)
3. Average desired distance between stopped cars (Wiedemann 99 Parameter CC0)
4. Headway time as a function of speed (Wiedemann 99 Parameter CC1)
5. Safety distance allowed before the driver moves closer to the vehicle ahead (Wiedemann 99 Parameter CC2)

The optimization was accomplished through the use of a genetic algorithm programmed in Visual Basic. The final set of calibration parameters DLCD, WTBD, CC0, CC1 and CC2 was 300 meters, 90 seconds, 1.5 meters, 0.8 seconds and 3.50 meters for peak time and 200 meters, 45 seconds, 1.5 meters, 1.0 seconds and 5.0 meters for midday traffic [16]. There is no discussion of the parameter ranges used in the genetic algorithm.

The vehicle speeds were then used to validate the models calibration. The results from runs using the default parameter values, optimized parameter values and the actual field data were compared at 8 different data collection sites. The absolute average difference between measured and simulated speeds before calibration was 1.86 percent with a root mean square error of 3.88. After calibration the absolute average difference between measured and simulated speeds was 0.84 percent with a root mean square error of 2.09. This shows that the calibration using the genetic algorithm was able to produce more accurate results than the default VISSIM parameter values. The researchers also concluded that drivers in Shanghai were more aggressive in lane changing compared with the default values in VISSIM [17].

3.1.2 VISSIM: A Multi-Parameter Sensitivity Analysis (2006)

This paper was presented at the 2006 Winter Simulation Conference by two researchers from the Department of Civil, Architectural and Environmental Engineering at the University of Texas at Austin. This study investigates the effect of 7 of the Wiedemann 99 car following parameters (CC0, CC1, CC2, CC4, CC5, CC7, and CC8) on the capacity of a freeway [5]. These parameters modify the behavior of four assumed driving modes: free-driving, approaching, following and braking. The authors use a higher level measurement such as capacity for calibrations, stating it is more effective than using lower level measurements because the higher level measurement is more likely to provide a global solution rather than a set of calibration parameters that work for some portions of the model but not others [5].

In this study capacity is defined as "the observed queue discharged in one hour immediately downstream of the bottleneck formation point on a single date during the evening peak period." The authors support this definition of capacity by referring to FHWA material [5]. Only one day of volume data is used to build the model and the field capacity values are taken from manual counts from video tapes of the bottleneck formation point. The site used for the simulations is the interchange of US 75 NB and SH190 near Plano and Richardson Texas [5].

The seven car following parameters evaluated in the experiment are outlined below [5, 13]:

1. **CC0 – Stopped Condition Distance**: desired distance between stopped vehicles. Default value of 4.92 ft.

2. **CC1 – Headway Time**: Controls the speed dependent portion of the desired safety distance between vehicles. Default value of 0.90 seconds.

3. **CC2 – ‘Following’ Variation**: Determines at what distance a driver will make an effort to approach the vehicle in front of him. Default value of 13.13 ft.

4. **CC4/CC5 – ‘Following’ Thresholds**: Control the upper and lower values of sensitivity to deceleration and acceleration of the preceding vehicle. Default values of +/- 0.35.

5. **CC7 – Oscillation Acceleration Rate**: Represents the desired acceleration during oscillation. Default value of 0.25 m/s^2

6. **CC8 – Stopped Condition Acceleration:** Determines the acceleration of a vehicle from a stopped condition unless it is outside the bounds of the predetermined maximum and minimum acceleration values for the vehicle class in which case they are used. The default value is 11.48 ft/s^2 which is the same as the maximum allowable acceleration for passenger cars.

For the experiment six parameter combinations were considered in the study and evaluated at five levels of each parameter. This resulted in 25 parameter pairs for each combination. The parameter ranges were bounded by values of 1/3 the calibration value and 3 times the calibration value. Six replicate runs were done for each combination for 150 observations for each combination. The parameter combinations were selected based on observed and logical relationships between the parameters. The parameter combinations considered were: CC0 and CC8, CC1 and CC4/CC5, CC2 and CC4/CC5, CC7 and CC2, CC7 and CC4/CC5, and CC7 and CC8 [5].

A two way complete model was used in the analysis of variance for each combination of parameters at a significance level of 0.05. The results for each combination were shown in an interaction plot displaying the mean capacity for each pair of values. In 2 of the 6 combinations interaction between the parameters was discovered. These combinations were CC0 and CC8 and CC1 and CC4/CC5. The impact on capacity of CC8 and CC4/CC5 was dependent on the respective values of CC0 and CC1. It was concluded that this was true because CC0 and CC1 are the two factors used in the calculation of *dx_safe* or the minimum headway in VISSIM. This means that for certain desired capacities there may be multiple optimal parameter solutions for the values of the 4 parameters listed above. In these cases the modeler must choose the best parameter set based on what best mirrors reality [5].

3.1.3 Microscopic Simulation Model Calibration and Validation, Case Study of VISSIM Simulation Model for a Coordinated Actuated Signal System (2003)

Park and Schneeberger present a case study outlining their 9 step process for calibration and validation of a simulation model from a 12 intersection section of highway in Fairfax, Virginia with an actuated signal system. Their model used the Weidemann 74 car following model instead of the Weidemann 99 model. The 9 steps in their process are: measure of effectiveness selection, data collection, calibration parameter identification, experimental design, simulation runs, surface function development, candidate parameter set generations, evaluation, and validation through new data collection. They assert that any “changes to parameters during calibration should be based on field-measured conditions and should be justified and defensible by the user.” [11]

The measures of effectiveness chosen for calibration and validation were a single lane travel time and a maximum queue length measurement. Data was obtained from the Virginia DOT and field measurements. The 7 parameters chosen for calibration and the ranges considered were [11, 13]:

1. **Emergency Stopping Distance**: Latest possible position for a vehicle to change lanes on a link. Range of 2.0–7.0 m.
2. **Lane-Change Distance**: Distance at which vehicles begin to attempt a lane change. Range of 150.0–300.0 m.

3. **Desired Speed Distribution**: The range of desired speeds chosen by drivers. Acceptable ranges of 30–60 mph, 35–55 mph, and 40–50 mph.

4. **Number of Observed Preceding Vehicles**: Determines how many vehicles ahead a driver can react to. Range of 1–4 vehicles.

5. **Average Standstill Distance (Ax):** Average desired distance between stopped cars. Range of 1.0-3.0 m.

6. **Waiting Time before Diffusion:** Maximum amount of time a vehicle can wait to change lanes before it is removed from the network. Values of 20, 40, and 60 second.

7. **Minimum Headway:** Minimum distance available for a lane change. Range of 0.5-7.0 m.

A Latin Hypercube design was used to create random samples of the chosen parameters that varied across their ranges. Latin Hypercube sampling is a method by which to generate random samples that effectively cover the sample space without having to generate as many samples as would be required by a truly random sampling process. In Latin Hypercube sampling each variable's range is divided into smaller ranges of values and then one sample is chosen for each combination of variables and ranges. An example of a Latin Hypercube sample for two variables (A and B) with four ranges of values each is shown in Figure 3 below.

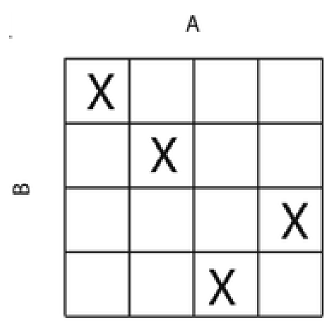


Figure 3: Illustration of a Latin Hypercube Sample [3]

In the study 124 cases were created with 3 values for each parameter. For each case 5 random seeded runs were performed for a total of 620 runs. After the runs a linear regression model was created with all of the parameters except for the desired speed distribution as the independent variables and the eastbound left lane travel time as the dependent variable. Then the Excel Solver was used to determine candidate parameter sets for the target travel time of 613.16 seconds. From the solver 8 solutions were obtained and 50 random seeded runs were performed for each set of parameters [11].

The 8 parameter sets were then evaluated based on the average eastbound left lane travel time and the simulation visualization. T-tests showed that for 6 of the 8 cases field conditions were replicate at least once in the 50 runs. Two of the cases were also found to be unsatisfactory because of unrealistic animations during the simulation. Only one parameter set was chosen as the best based on these evaluations [11].

For validation the chosen parameter sets maximum queue length at an intersection was compared to the field data. It was found that the field maximum queue length was within the simulated distribution but in the top 10% of that distribution. The calibration method used was effective in replicating the field conditions far better than by using default values. The authors stress that examining the visualizations of the simulation runs is a necessary step as well as looking at measures of effectiveness [11].

3.1.4 Development and Evaluation of a Procedure for the Calibration of Simulation Models (2005)

In this report Park and Qi consider an alternate method of calibrating a simulation model. The test model used is of a single, actuated intersection in Virginia with single lane approaches and exclusive right turn lanes in all directions. The steps for calibration were: model setup, initial calibration, feasibility test, parameter calibration with a genetic algorithm, and model evaluation. This procedure does not use the linear regression method used in Park's previous paper. The measures of effectiveness used for the calibration were the average travel time for the southbound through and left turn movements [10].

The initial evaluation was done by running multiple random seeded runs of the model with the default parameters. The average travel time was found to be far less than the field data thus calibration was required. To determine the critical parameters for calibration two criteria were used: trial and error tests to determine if a parameter affects the measure of effectiveness and traffic engineer's judgment of parameters that should not affect the model. For this case 8 parameters and their ranges were initially chosen for calibration. These parameters are listed below:

1. Simulation resolution (1-9 time steps per second)
2. Number of observed preceding vehicles (1-4)
3. Average Standstill Distance, Ax (1-5 m)
4. Additive part of desired safety distance, Bx_Add (1-5 m)
5. Multiplicative part of desired safety distance, Bx_Mult (1-6 m)
6. Priority rules for minimum headway (5-20 m)
7. Priority rules for minimum gap time (3-6 sec)
8. Desired speed distribution (30-40 or 32.5-37.5 or 27.5-42.5 mph)

Once again the Latin Hypercube sampling method was used to select 200 parameter sets to be tested. For each case 5 random seeded runs were completed for a total of 1,000 runs. After the runs a one-way ANOVA procedure was used to measure the sensitivity of the results to each parameter. The desired speed distribution and minimum gap time were chosen as critical parameters. Following this analysis 9 parameters with adjusted ranges were considered for calibration in the genetic algorithm. The additional parameter was the maximum look-ahead distance with a range of 200-300 meters [10].

The genetic algorithm takes an iterative approach in order to obtain the optimal set of parameters utilizing the theory of evolution and genetics. After each run, or generation, the results are measured and assigned a level of fitness. Then based on this level of fitness parameter values are modified through selection, crossover and mutation in order to obtain a new set of parameters, or generation, and a hopefully higher level of fitness. Once the parameters reach a certain level of fitness or run through the maximum number of generations the algorithm is stopped. The genetic algorithm obtained parameter set was able to outperform both the default and best guess parameter sets in matching field data. Although, the authors note that these results were only tested against a single measure of effectiveness, travel time, and may not be reflective of other measures such as queue length or delay [10].

3.1.5 Application of Microscopic Simulation Model Calibration and Validation Procedure: A Case Study of Coordinated Actuated Signal System (2006)

This study, done by Park et al., repeats the work from the previous study on a larger scale network of 12 intermediate intersections with coordinated, actuated signals. The site chosen was on U.S. Route 50 in Fairfax, Virginia, the same site used in the Park and Schneeberger paper. Like in the Park and Schneeberger paper, travel time data was used for calibration and queue length data was used for validation. The difference between the studies is the method of calibration used. In this case a genetic algorithm was used for calibration as opposed to the linear regression method used before. Also, the calibration method was tested for both VISSIM and CORSIM models [12].

For the VISSIM calibration the same 9 parameters from before were tested as well as 5 more:

1. Waiting time before diffusion (20-40 sec)
2. Minimum headway (.5-7 m)
3. Maximum deceleration (-5 - -1 m/s^2)
4. Reduction rate (20-80 m)
5. Accepted deceleration (-1.5 - -.1 m/s^2)

The ranges for the original 9 parameters were relatively unchanged aside from the 3 speed distributions which were shifted upward to reflect a mean speed of 45 mph [12].

Once again, Latin Hypercube sampling was used to produce 200 parameter sets with 5 random seeds for each for a total of 1,000 runs. The travel time results from these runs showed that the field travel time was within the range of the chosen parameters. The genetic algorithm was then run for these parameters and ranges and converged to a solution in 10 generations. Then 100 random seeded runs were done for this solution parameter set. This first solution produced travel times that matched the field data, but not queue lengths so an additional solution was created using the genetic algorithm. The second solution's results from 100 random seeded runs matched both the field travel times and queue lengths. In the runs for both parameter sets no unusual visualizations were observed. For both sets of runs the 2 most influential parameters were the additive part of safety distance, ax, and the desired speed distribution [12].

3.1.6 A Methodology to Calibrate Microsimulation Models for Traffic at Signalized Intersections with a High Degree of Heterogeneity and Lack of Lane Discipline (2008)

This paper examines how to calibrate a VISSIM model for unusual conditions such as those present in the 3 selected intersections in India. To determine which parameters to include in the calibration a sensitivity analysis was completed. Delay was measured after individually varying each parameter by 10% and any parameters with a significant impact on the resulting delay were included in the calibration process. Preliminary parameter ranges were also set by incrementally increasing and decreasing the parameters to determine at what value they produce unrealistic delay results, in this case twice the field delay. Also, even if a parameter did influence delay but only did so by producing unrealistic situations, such as vehicles jumping red lights, it was not included for calibration [6].

Both the Wiedemann 74 and 99 car following models were examined and ultimately 9 parameters were examined for the Wiedemann 74 model and 10 for the Wiedemann 99 model. Because this study was examining individual intersections with unusual characteristics the parameters chosen for calibration did vary from the previous studies. Parameters such as the number of observed preceding vehicles and priority rules for minimum headways and gap times were left out while parameters such as minimum lateral distance for passing were included. Also, in this study a different model was used for vehicles reactions to traffic signals which introduced 3 new parameters for calibration: Ambert_alpha, Amber_beta1 and Amber_beta2 [6].

A genetic algorithm was used for calibration in two ways. First each of the three intersections was calibrated individually and then they were calibrated as a group. The parameters found from the group calibration were acceptable for two of the three intersections. The calibrations using the genetic algorithm were successful. The simulation delay at all 3 intersections matched the field delay when the individually calibrated parameters were used. The calibrations using the Wiedemann 99 parameters outperformed those using the Wiedemann 74 parameters [6].

3.1.7 Development and Evaluation of a Calibration and Validation Procedure for Microscopic Simulation Models (2004)

This study more generally examined procedures for calibrating simulation models for VISSIM, CORSIM and PARAMICS on two test sites. One site was an actuated, signalized intersection and the other was a freeway segment with a reduced speed zone. The intersection site used the Wiedemann 74 parameters and the freeway site used the Wiedemann 99 parameters [8].

This study was conducted similarly to the previous papers by Park et al. and produced similar results. The ANOVA results showed that the two most important parameters influencing travel time in the intersection model were the desired speed distribution and the minimum gap time. Latin Hypercube sampling was used to test the feasibility of the parameter ranges and a genetic algorithm was used to optimize the parameters [8].

After the calibration, 4 parameter sets were compared: the default set, the best guess set, the Latin Hypercube based best set, and the genetic algorithm optimized set. The default and best guess parameter sets were not adequate, but both the Latin Hypercube best set and the genetic algorithm optimized set met the calibration and validation criteria. The genetic algorithm parameter set did do better than the Latin Hypercube parameter set but not enough so to justify the additional time and effort involved in creating the optimized parameter set. A final list of important parameters in VISSIM was included in the appendix and is recreated below [8]:

1. Waiting time before diffusion
2. Minimum headway (front/rear)
3. Maximum deceleration
4. Reduction rate
5. Accepted deceleration

6. Number of observed preceding vehicles
7. Maximum look-ahead distance
8. Average standstill distance, Ax (Urban only)
9. Additive part of desired safety distance (Urban only)
10. Multiplicative part of desired safety distance (Urban only)
11. Average standstill distance, CC0 (Freeway only)
12. Headway at a certain speed, CC1 (Freeway only)
13. Longitudinal Oscillation, CC2 (Freeway only)
14. Start of the deceleration process, CC3 (Freeway only)
15. Oscillation acceleration rate, CC7 (Freeway only)

3.2 Analysis

These seven studies are a good showcase of the current practices involved in calibrating traffic models in VISSIM. Each followed a generally similar outline in their calibration process. This process includes running the model under default parameters to ensure that the model needs further calibration, selecting the parameters to be calibrated, calibrating the selected parameters so that the model results match the field data, and validating the calibration against additional field data. However, differences exist among the chosen parameter calibration procedure. In the studies the techniques used included using the "best guess" parameters, producing random sets of parameters and selecting those that gave the best results, producing random sets of parameters and using the results to create a regression model with which to solve for the calibrated parameter values, and using a genetic algorithm to create an optimized set of parameters. All of these techniques have their own merits and many have been shown to produce equivalent results.

What is not clearly addressed in many of these calibration methods is how to select the parameters to calibrate.

As discussed in Chapter 2 there are up to 50 parameters available to change in any VISSIM model, but the maximum number of parameters calibrated in any of the reviewed studies was only 12. This is likely a reasonable number of parameters as for any given model it is unlikely that all 50 parameters significantly influence the model results. The challenge is to determine which parameters are necessary to calibrate.

The methods used in the reviewed studies to select the parameters for calibration varied and were rarely, specific or precise. Some studies [5, 9, 11, 12] did not even reference how the parameters were chosen. Others [8, 10, 17] referenced using things such as "past experience" or "engineering judgment" to aid selection of the parameters. However, there is no guarantee that the current model being calibrated is not a new or unusual case where this experience may lead to incorrect assumptions.

Out of all of the methods described in the studies only two seemed effective at correctly determining which parameters to calibrate. The first involved using ANOVA on simulation run results with random parameters to determine which parameters were most influential [8]. The second modified each parameter by 10% of its default value and measured the change in the delay for the network [6]. If the change in the parameter value modified the delay for the network then the parameter was chosen for calibration. These two methods are far more promising but little explanation or validation is given for their use. In the next chapter an alternative procedure for selecting the parameters will be explained in detail and in Chapter 5 this procedure will be illustrated on an existing VISSIM model.

CHAPTER 4

GENERAL PROCEDURE

The goal of this project is to create a process to select the parameters that should be included for a model's calibration. These parameters may be different for each model and so the process needs to be flexible and usable regardless of the model being calibrated. The process proposed consists of four steps with the last two being iterative. The steps in the process are:

1. Initial parameter selection
2. Measures of effectiveness selection
3. Monte Carlo experiment
4. Sensitivity analysis and parameter elimination
   (Repeat steps 3 and 4 until stopping criteria met)

4.1 Initial Parameter Selection

In the first step of the process certain parameters can be eliminated immediately. The decision to eliminate a parameter in this step should be based on a priori knowledge that the parameter will not meaningfully, if at all, impact the simulation accuracy. Parameters may also be eliminated if the model they are associated with is not used. Examples of VISSIM parameters that could be eliminated at this step and the reason for elimination are listed below:

- **Temporary lack of attention parameters**: there is a lack field data available to calibrate the parameters and the VISSIM default value both parameters is 0.0, i.e. the temporary lack of attention model is not used.

- **One of the car following models (Wiedemann 74 or Wiedemann 99):** Wiedemann 74 is related to arterial operations and Wiedemann 99 to freeway operations. If the model does not include one type of facility then the parameters related to that model need not be included.

- **Lateral behavior parameters:** where only cars and other heavy vehicles interact on the roadways there is no lateral behavior present.

These parameters include just a few of the potential parameters that could be eliminated before further study. If it is unclear whether a parameter should be eliminated at this step of the process it is recommended that the parameter remain in the experiment or conduct a limited sensitivity experiment to quickly determine if the parameter in question could potentially affect the measures of effectiveness of the model. An example of an experiment for this purpose could be running a set of simulation runs (including replications) for increasing values of the parameter and observing the resulting values for the measures of effectiveness. If all of the other parameters remained constant the results should be consistent among the runs. If they are not consistent then the parameter should be left in for consideration in the first Monte Carlo experiment. Caution must also be exercised in such limited experiments as the potential for cross effects with another variable may be missed.

4.2 Measures of Effectiveness Selection

Before any simulations can be run the measures of effectiveness for the network must be selected. As discussed in Chapter 2 the measures of effectiveness can be any number of, and any combination of, travel times, flows, capacities, delay values, and queue lengths. Measures of effectiveness should be selected such that effects on individual parts of the network, such as intersections or ramps, and effects on the entire network are captured. Common selections could include end to end travel time measurements, travel time measurements over the most commonly traveled routes, delay measurements at intersections, queue lengths at bottlenecks, queue lengths at major intersections, etc… Analyst judgment is required in the selection of measures of effectiveness for the particular simulation under study. However, in the initial stages, it is generally recommended to include a wide cross section of potential measures, paring down the measures in later analysis if the fail to be informative.

4.3 Monte Carlo Experiment

Once the parameter list has been narrowed in the first step the remaining parameters must be tested to determine likely influence on the model. In order to do this a Monte Carlo experiment is used. A Monte Carlo experiment is an experiment based on analyzing the results produced from a random generation of inputs. For this case the ranges of each parameter must be defined and then random values are produced in order to investigate the different parameter combination scenarios. The procedure for doing this involves three steps:

1. Parameter range selection
2. Random parameter generation
3. Simulation runs

4.3.1 Parameter Range Selection

There is no exact method to determine the ranges for the remaining parameters. The ranges must be determined through a combination of past experience, information from the VISSIM documentation, and engineering judgment. The goal should be to make the range of a parameter large enough to cover all feasible values of the parameter without including values which introduce impossible or flawed behavior in the model. Impossible or flawed behavior could include things such as drivers running red lights or vehicles driving over the top of one another in an intersection. When the analyst is uncertain of a reasonable parameter range it is recommended to use a larger rather than smaller range and if necessary narrow the ranges later in the process. The VISSIM documentation can provide insight into how certain parameters affect the model and thus which values are realistic for each parameter. The documentation can also help clarify how changing a parameter's value from the default value will alter the simulation results. For example in the VISSIM help file an explanation of the minimum look ahead distance says: "The min. value is important when modeling lateral vehicle behavior. Especially if several vehicles can queue next to each other (e.g. bikes) this value needs to be increased. The value depends on the approach speed. In urban areas it could be 20-30m (60-100 ft)." [13] Thus, modifying this parameter may likely have little influence on the model where there is no lateral behavior present and it also gives us a reasonable range for this parameter in an urban area with lateral behavior.

Finally, engineering judgment must be used to modify the ranges used by others or from the VISSIM documentation to tailor ranges to the specific model. For instance, if for a model where drivers are very knowledgeable and have been observed to have a high likelihood of moving into the correct lane for their route further upstream than would be assumed by default the parameter "lane change distance" assigned to each connector in the network might be given a range that extends much further than in other models. As part of this process ranges can always be narrowed and refined eliminating values that produce unrealistic behavior in the simulation during this first generation of parameters.

4.3.2 Random Parameter Generation

Once the ranges have been set for all of the remaining parameters the values for these parameters must be randomly generated and a collection of VISSIM input files created. There are many ways to accomplish this task. For this study Microsoft Excel 2007 was used to randomly generate the parameter values, and the VISSIM input files were generated using a PERL script. To generate the random values in Excel two functions were used. For integer values such as "number of observed vehicles" the "RandBetween(x,y)" function was used. This function returns a random integer between the input values of x and y. For non-integer values the function "Rand()" was used. This function returns a random value between 0 and 1. The returned value was then multiplied by the absolute size of the range of each parameter and added to the minimum value of each range. For example:

$$Minimum\ Headway = Random\ value\ between\ [1.64, 25.0]$$

$$Minimum\ Headway = Rand() * abs(25.0 - 1.64) + 1.64$$

These functions were used to generate 1,000 random values for each parameter. More or less than 1,000 values could be generated depending on the specific case, but 1,000 values is a sufficiently large enough number to cover the sample spaces for each parameter and a reasonable enough number to realistically run the simulations within an adequate time limit.

Before the parameters could be put into the VISSIM input files they had to be converted from English to metric units. To accomplish this the "Convert()" function was used in Excel to quickly convert all of the values to metric units. The PERL script used to create the input files used a template VISSIM input file created with the model's geometry and default parameter values and a comma delimited Excel sheet containing all of the parameter values in metric units as inputs. The script would then search for the line in the VISSIM file pertaining to each parameter value and replace the existing value with the value from the Excel sheet.

4.3.3 Simulation Runs

After all 1,000 new VISSIM files had been created a Visual Basic script was written in Excel 2007 to run all of the files. The script was a modified version of the "multi-run" script provided with VISSIM [14]. It ran a simulation for each listed input file and then copied and renamed the created output files according to their run number (1-1000) and placed them into a new directory.

4.4 Sensitivity Analysis and Parameter Elimination

4.4.1 Plotting the Results

Once all of the simulations have been run and their respective output files created the results must be analyzed in order to determine which parameters are insignificant. Before the results can be effectively analyzed they must be organized into a form which is easier to work with than the output files created by VISSIM. Again, Excel 2007 was used for this purpose.

In our example, a VBA script was used to import all of the output files into worksheets in Excel, with the worksheets divided by the measure of effectiveness type (e.g. travel time, delay, etc…). Then an additional script was run to copy the necessary data from the imported reports onto new worksheets with the data better organized for manipulation within Excel. After completion of these steps the data was ready to be converted into useful plots.

The data should then be plotted on scatter plots with the measure of effectiveness value on the Y axis and the parameter value on the X axis. This means that there will be a unique scatter plot for each parameter and measure of effectiveness combination. For example, if the simulation is run with 30 randomly varying parameters using 3 different travel time measurements and 2 different queue length measurements as measures of effectiveness there would be 90 independent travel time scatter plots and 60 independent queue length scatter plots, for a total of 150 scatter plots. The scatter plots should also include a best fit line to aid in analysis. For this study the plots were created and placed onto new worksheets; each worksheet containing a different measure of effectiveness type. Within each worksheet the data was separated into columns for each different measure of effectiveness within the type (e.g. Travel Time Northbound, Travel Time Southbound) and rows for each different parameter.

Due to the number of plots that need to be created it is important that only a limited number of measures of effectiveness are used in this step of the process regardless of the number recorded during the simulations. The additional data can be used later to verify or further explain the obtained results. The measures of effectiveness used in this step should be the most important ones to the models successful calibration or the ones that have the best field data to measure against.

4.4.2 Analyzing the Results

After the scatter plots are created the results can be analyzed and parameters can be eliminated. One of the most useful tools to determine whether parameters are significant or not is a simple visual inspection of the scatter plots. If all of the points generally lie around a horizontal line then the parameter is most likely insignificant, but if the points follow a trend other than a flat line then the parameter is most likely significant.

A more mathematical approach to accomplish a similar task is to measure the effect that the parameter has on the mean of the measure of effectiveness value. For example, if the parameter is insignificant then the points will follow a horizontal line and the effect on the mean will be zero, but if the parameter is significant then the mean of the values of the measure of effectiveness should change as the parameter changes resulting in a measurable effect on the mean. The value of the effect on the mean is equal to the slope of the best fit line of the scatter plot multiplied by the absolute value of the range of values for the given parameter. This can be obtained easily in Excel by using the "slope(X,Y)" function which returns the best fit slope for any number of corresponding X and Y coordinates. These values can then be used to rank each parameter based on its effect on the mean of each measure of effectiveness.

$$Effect\ on\ the\ Mean = Slope((MOE\ Values)_{1\to n}, (Parameter\ Values)_{1\to n})$$
$$* abs(\ Parameter\ Upper\ Bound - Parameter\ Lower\ Bound)$$

Variability due to the parameter should also be considered. That is, does the spread of the points around the mean change. If the variability increases or decreases with respect to the parameter than the parameter should remain in the analysis, even if the impact on the mean value is minimal. For this study the significance of the impact of the parameter on variability was determined through visual inspection of the scatter plots.

4.4.3 Parameter Elimination

Eliminating parameters from consideration for calibration is the ultimate goal of the procedure and the most important step. Special care must be taken that significant parameters are not eliminated and that too many borderline significant parameters are not eliminated at one time resulting in hard to understand results in the next set of runs. After the first set of runs it is advised that only the most insignificant parameters are eliminated. Any parameter that displays the slightest hint of significance should remain in the experiment for further study. Additionally, any parameter that intuitively seems as if it should be significant but does not appear to be significant in the results should not be eliminated, allowing for confirmation of significance in the next iteration. The number of variables to be eliminated per iteration is ultimately an analyst judgment. The fewer parameters eliminated the more iterations and computations required to reach the final data set while the more parameters eliminated the higher the likelihood a significant parameter will be reduces. While the parameter reduction should be a function of the findings a general guideline is that number of parameters eliminated should not exceed one-third of the total parameter set. However, this not a firm rule and based on experience gained during this study.

4.4.4 Iteration

The parameters left after the first elimination are not the final parameters to be considered for calibration. Additional sets of runs must be completed in order to narrow the list to the optimum set of parameters for calibration. Before the next set of runs can be done the ranges of the parameters that were kept after the first elimination should be reexamined. This can be done by examining the scatter plots for each parameter. If there are obvious abnormalities in the data, such as extremely high travel times, then the range for that parameter might need to be narrowed. Large numbers of errors recorded during the simulation might also be an indicator that one or more parameters are being set to an unrealistic value. Similarly if there is reason to believe that the range of values for that parameter should be larger, then that range should be modified as well.

Once all of the parameter ranges have been examined the previous steps must be repeated. First, 1,000 new sets of parameters must be generated with the eliminated parameters set to either their VISSIM default values or some other pre-defined, field measured values for the specific model. Then the new parameter sets can be used to create the new VISSIM input files and run the simulations. The second round simulation results should be examined in the same manner as the first. To avoid an unintentional analyst bias in the final parameter selection it is useful to create a rule that determines if a parameter should be considered significant or not. An example rule might be "if parameter X causes a 5% change in the mean of the value for measure of effectiveness Y then parameter X is significant." A rule such as this would be specific to each model and measure of effectiveness and could not be applied generally. The analyst must decide what level of impact is deemed significant for the particular study. For instance in a more generic planning study a 10% error may be tolerable and therefore the effort and time should not be spent to calibrate parameters whose effect is under 10%. Whereas in a detailed design application it may be desirable to consider any parameter whose possible impact on the simulation measures may be within just a few percent.

The second round is not necessarily the end of the process. If it is still unclear which parameters to include in the final set and there is merit to reducing the number of parameters to keep then subsequent iterations of the process should be completed. Ultimately judgment must be used to decide which parameters cannot be left out, but the above procedure should aid in the investigation of the specific effects of each parameter and in the elimination of parameters that obviously have no effect on the model. For the model examined in this study three iterations were deemed sufficient but for other cases additional iterations may be required. Additional study would be beneficial to determine how many iterations may be required for different cases and additional guidance on parameter elimination rules. The end of the process is reached when the list of parameters for calibration is sufficiently short that the parameter calibration may be completed with a reasonable timeframe and does not include any parameters that are insignificant to the model.

CHAPTER 5

CASE STUDY: COBB PARKWAY MODEL

5.1. Introduction

In this chapter a case study will be presented demonstrating how the procedure detailed in chapter 4 was applied to an actual VISSIM model. In the beginning of this chapter the model will be described in detail. Then each step of the process will be explained as it is applied to the model. The steps include the initial parameter selection, measures of effectiveness selection, and finally the results of the iterative simulation runs and parameter elimination. The process will be completed twice, once for the uncongested case and then again for the full volume, near congestion case.

5.1.1 Model Selection

To illustrate how the procedure is implemented in practice a model was selected for a case study. A preexisting model of Cobb Parkway in Atlanta, GA was selected for a variety of reasons. The most obvious reason for selecting this model is that it has already been constructed, calibrated and validated. Also the characteristics of the network make it a great example since it is a high volume, near congestion, signalized urban arterial. The specifics of the model will be discussed later.

The model selected, as mentioned in the introduction, was used for two different cases. In the first case all of the input volumes were left at their actual, AM peak hour field recorded values. In the second case the input volumes for the model were uniformly reduced by 25% to create an uncongested situation. This lower volume case allows for an initial exploration of the impact of demand on parameter selection. A higher congested scenario is not examined as part of this effort. The two cases will be referred to as the 100% volume case and the 75% volume case respectively.

5.2 Model Design

5.2.1 Model Location and Characteristics

The Cobb Parkway model is an existing model of Cobb Parkway in Cobb County, GA (Figure 5). The model extends from just past Lake Park Drive in the north to just past Akers Mill Road in the south crossing a total of eleven signalized intersections. Cobb Parkway has four lanes traveling in each direction and is the main artery for Cobb County, running parallel Interstate 75. A satellite image, map, and VISSIM representation of the model site are shown in Figure 4, Figure 5, and Figure 6, respectively. The model was constructed using balanced 2004 intersection count data for the AM peak hour traffic volumes obtained from the Cobb County Department of Transportation. Existing signal timings were used with NEMA signal controllers. The speed limit on the road is 45 mph, and the desired speed of the drivers on the network varies between 42.3-48.5 mph. This model has previously been validated against the observed data from the network. The model was used, unmodified, as the basis for the experiment. The only changes made to the model as part of this study were the parameter changes for the experiment, volume and desired speed changes for the various scenarios, and the addition of travel time measurement zones and queue counters.

Figure 4: Satellite Image of Cobb Parkway [1]

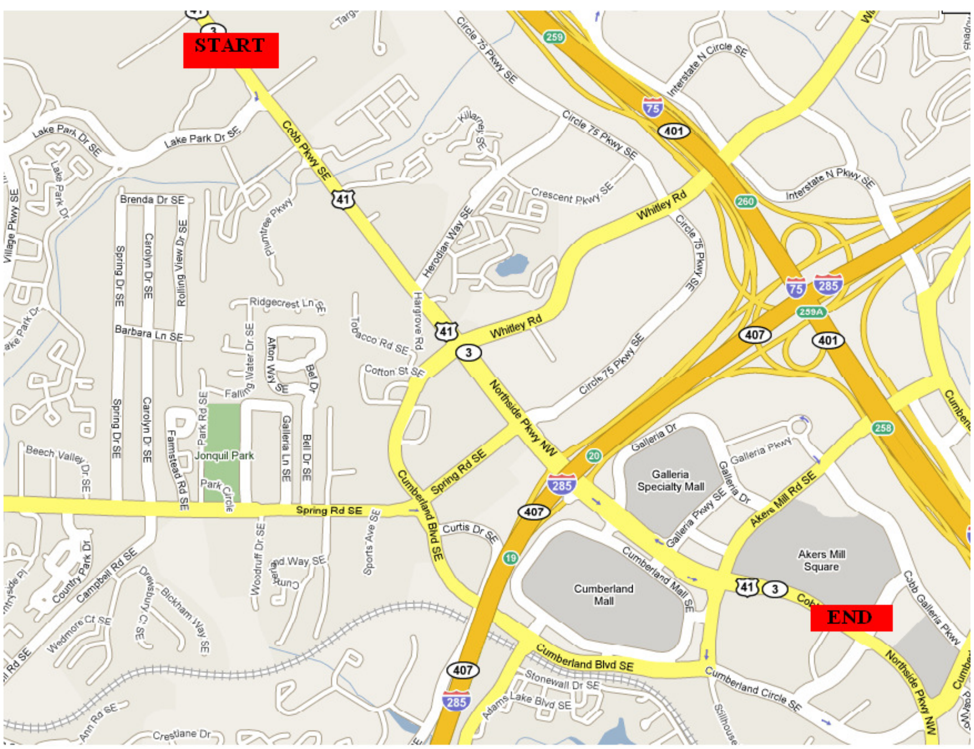


Figure 5: Map of Model Location [1]

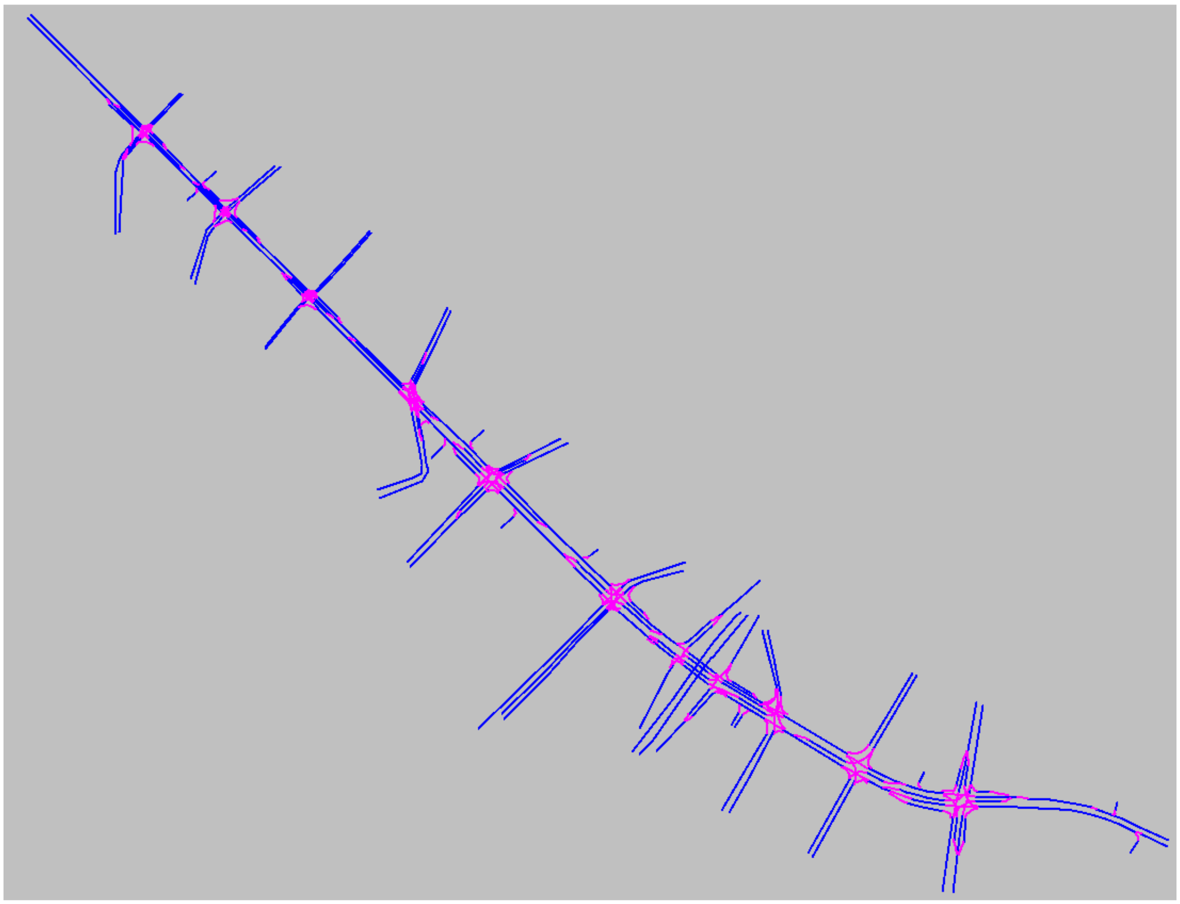


Figure 6: Network Representation in VISSIM

5.2.2 Calibration with a Genetic Algorithm

This model was calibrated by previous researchers using a genetic algorithm. The parameters that were used for calibration are listed in Table 3 below along with their ranges for calibration and final calibrated values. The algorithm was run for twenty generations. For that calibration effort the researchers had conducted an abbreviated sensitivity analysis and review of previous literature to select the parameters for calibration.

Table 3: Existing Calibration Data for the Cobb Parkway Model

Parameter	Range	Final Value
Maximum Look Ahead Distance	410.10 - 1230.31 ft	674.7 ft
Number of Observed Vehicles	1 - 4	2
Average Standstill Distance, Ax	3.28 - 9.84 ft	6.27 ft
Additive Part of Safety Distance, Bx_Add	1.0 - 2.5	1.05
Multiplicative Part of Safety Distance, Bx_Mult	1.0 - 3.5	1.08
Maximum Deceleration (own)	-19.69 - -6.56 ft/s^2	-15.03 ft/s^2
Maximum Deceleration (trailing)	-14.76 - -4.92 ft/s^2	-11.29 ft/s^2
Accepted Deceleration (own)	-4.92 - -1.64 ft/s^2	-3.77 ft/s^2
Accepted Deceleration (trailing)	-4.92 - -1.64 ft/s^2	-3.77 ft/s^2
Reduction Rate (own)	50 - 150	100.00
Reduction Rate (trailing)	50 - 150	100.00
Emergency Stop Distance	8.20 - 24.61 ft	23.60 ft
Lane Change Distance	328.08 - 984.25 ft	963.10 ft

5.3 Initial Parameter Selection

The initial parameter selection step is used to determine which parameters can be eliminated from consideration immediately. The characteristics of the model can have a heavy influence on this step of the process. For the Cobb Parkway model 28 of the available parameters were eliminated in this step leaving 22 parameters to consider for calibration. The reasons for eliminating each of the 28 parameters are described in the following sections, organized by parameter type. For the complete list of parameters available the reader is referred to Chapter 2.

5.3.1 Base Distributions

There are five base distributions able to be modified: the maximum and accepted acceleration and deceleration functions for each vehicle type and the desired speed distribution range for each traffic composition. The desired speed distribution range should not be eliminated, as previous experience and literature clearly indicate at least a potential significance of this variable. The acceleration functions are eliminated and fixed at their default values because they are fixed according to the mechanical capabilities of the average vehicle on the network. At this stage little justification exists for changing the default values. Attempting to modify the acceleration functions is also unnecessary as the driver's acceleration decisions are likely dominated by the car following model due to the close spacing of signals and level of congestion.

5.3.2 Following Behavior Parameters

Of the 18 car following parameters 12 can be eliminated. The two temporary lack of attention parameters can be eliminated and fixed at values of 0.00 because this type of behavior is not included into the Cobb Parkway model, as discussed previously. The choice of car following model can be set to the Wiedemann 74 model as this model is intended for signalized urban arterial simulation [13]. The Wiedemann 99 model is intended for freeway applications [13] so it is disregarded. The no interaction model is a model where vehicles are unaware of any other vehicles and is used for simplified pedestrian behavior [13]. Using this model would would lead to an unrealistic motor vehicle behavior. Since only the Wiedemann 74 model is used all 9 of the Wiedemann 99 model parameters can be eliminated.

5.3.3 Lane Change Behavior Parameters

The general lane change behavior can be set to free lane selection as Cobb Parkway (as with most US arterials) does not have a designated "fast lane" and vehicles often pass each other on both the left and right sides. This selection also eliminates the parameter "to slower lane of collision time above" as this parameter is only used in conjunction with right-side rule as opposed to free lane selection behavior. All of the other lane change parameters cannot be eliminated.

5.3.4 Lateral Behavior Parameters

All of the lateral behavior parameters can be eliminated as there is no lateral behavior present in the model. To support the supposition that lateral behaviors do not affect the model a test experiment was run. The model was run with all of the parameters fixed and then again with all of the parameters fixed except the lateral behavior parameters: desired position at free flow was set to "any," observe vehicles in the next lane was selected, diamond shaped queuing was selected, overtaking on the same lane was selected, and the minimum lateral distance was one meter. End-to-end travel times were recorded in each direction on Cobb Parkway and averaged across five replicate runs. The results were almost identical for both runs, see Table 4, indicating that the lateral behaviors do not affect the simulation results. For the rest of the procedure the lateral behavior parameters will be left at their default values.

Table 4: Comparison of Average Travel Times with and without Lateral Behavior Parameters

	Southbound Travel Time (5 run avg.)	Northbound Travel Time (5 run avg.)
No Lateral Behavior	273.1	305.3
With Lateral Behavior	272.6	309
% Difference	0.18%	1.21%

5.3.5 Signal Control Behavior Parameters

The amber decision model was set to the continuous check model and the one decision model and its associated parameters, α, β_1 and β_2, were eliminated. These parameters were eliminated because field data was not available to calibrate the one decision model accurately.

5.3.6 Connector Parameters

The desired direction parameter can be eliminated and set to "All" as when routing decisions are in effect this parameter has no affect as explained in the VISSIM documentation [13].

5.4 Measures of Effectiveness Selection

For the model's measures of effectiveness five travel time segments were chosen. The travel time segments were chosen as the primary measures of effectiveness because travel time data is straightforward, easily interpreted, and should reflect changes to the model. It is also straightforward to verify that the data is realistic based on segment lengths and vehicle speeds.

The five travel time segments include two end to end segments, a segment over the most traveled route on the network, and two short segments through two traffic signals. The segments are shown in more detail below.

Segment #1 is the southbound end-to-end segment. It is 11,294.1 feet long and crosses 10 intersections. Segment #2 is the northbound end-to-end segment. It is 11,333.5 feet long and also crosses 10 intersections. Because these segments are not heavily traveled (i.e. a limited number of vehicles actually travel the entire length of the arterial) 40 probe vehicles were added to travel on segment #1 and 20 were added to travel on segment #2. The probe vehicles had the same characteristics and behavior assigned to them as all of the other vehicles on the network. These additional probe vehicles resulted in around 96 vehicles per hour being recorded on segment #1 and 40 vehicles per hour being recorded on segment #2. Segments #1 and #2 are shown in Figure 7 below.

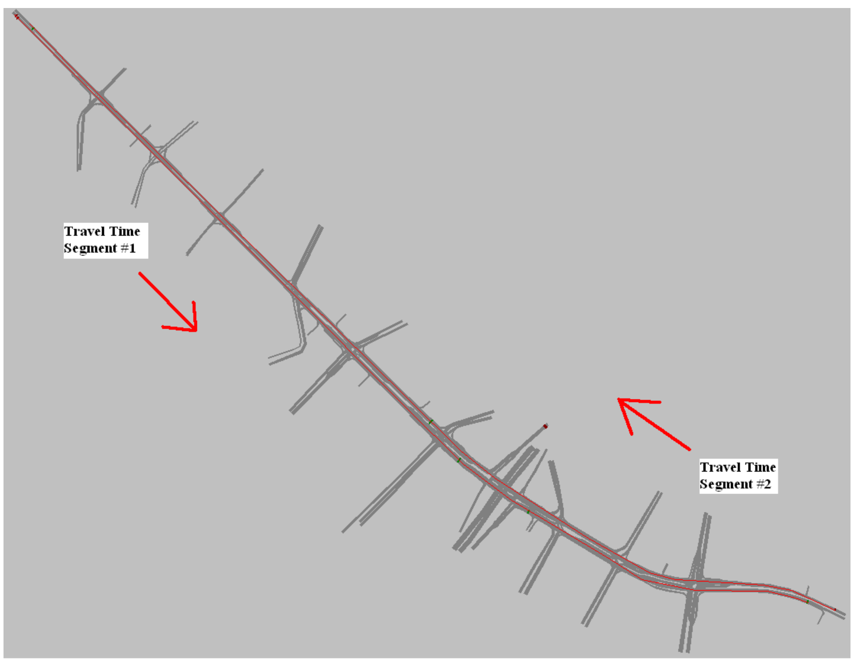


Figure 7: Travel Time Segments #1 and #2

The third segment is representative a typical commuter route. It is 6954.6 feet long and covers the most heavily traveled route on the network, from the northern arterial entrance to the intersection of Cobb Parkway and I-285. Over 640 vehicles per hour are recorded traveling across this segment providing a large sample size to calculate the average travel time across the segment. The segment is shown in Figure 8.

Figure 8: Travel Time Segment #3

Segments #4 and #5 are shorter segments at 1669.8 feet and 1425.9 feet and they cover 2 heavily traveled routes from the I-285 exit ramp to Cobb Parkway northbound and southbound. Each route goes through 2 traffic signals. Over 240 vehicles per hour travel on segment #4 and over 480 vehicles per hour travel on segment #5 providing excellent sample sizes to calculate average travel times. Segments 4 and 5 are shown in Figure 9.

Segment #5 is unique to the corridor because it covers 2 intersections that regularly have long queues and occasionally will experience cycle failures. These characteristics can lead to higher levels of variability in the travel time over the route than seen on other routes, providing a potentially different insight into the parameter effects.

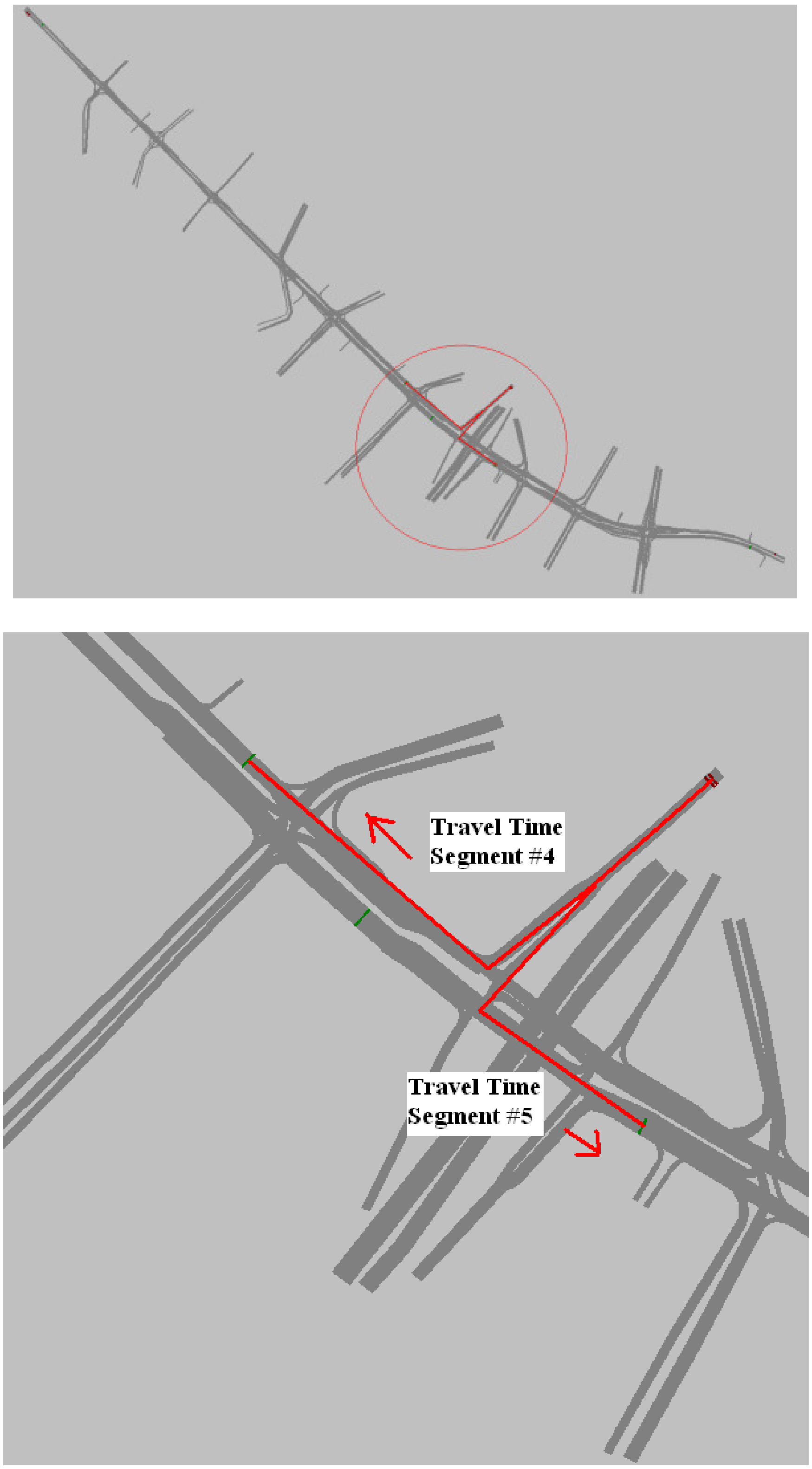


Figure 9: Detail View of Travel Time Segments #4 and #5

5.5. Parameter Range Selection

Before random values can be created for the parameters their ranges must be defined. It is possible to perform the parameter range selection in iterative steps as described in the previous chapter. However, initial parameter ranges may be selected based on previous experience, published literature, and initial test simulations runs to explore parameter feasibility. The first set of ranges was determined by examining the VISSIM documentation and ranges used from previous studies. The ranges selected were chosen such that they were always greater than any previously used range, but within any limits described in the VISSIM documentation. Also, it was ensured that the ranges were set so that they included any VISSIM default or previously used values for each parameter. Example of range selection for two parameters, the average standstill distance, ax and the additive part of safety distance, bx_{add}, are shown in Table 5. In the tables are the various values and ranges used in the determination of the chosen ranges for this study as well as the final chosen range.

Table 5: Example Data Used to Define Ranges

Average Standstill Distance, ax	
	Value/Range (ft)
VISSIM Default	6.56
Calibrated Cobb PKWY	6.27
Study #1 [6]	0.00 - 13.12
Study #2 [11]	3.28 - 9.84
Study #3 [12]	3.28 – 16.40
Study #4 [10]	3.28 – 16.40
Chosen Range	**0.0 - 20.0**

Additive Part of Safety Distance, bx_{add}	
	Value/Range
VISSIM Default	2.00
Calibrated Cobb PKWY	1.05
Study #1 [6]	0.00 - 4.00
Study #2 [12]	1.0 - 5.0
Study #3 [8]	2.0 - 2.5
Study #4 [10]	2.0 - 2.5
Chosen Range	**0.0 - 8.0**

After completing a set of initial simulations with parameters drawn from the initial ranges it was clear that many of them needed to be modified. Ranges were modified if some of the values led to unrealistic travel time values in the model or if the ranges appeared to be larger than necessary. For example, In Figure 10 below for standstill distances set to values larger than 10 feet the travel times (Travel Time Route #5) exhibits unrealistically high maximum values. Travel time segment #5 is a short segment through two intersections and the distance between the vehicles stopped at an intersection has a significant effect on the travel times. Because of this the maximum value of the range was lowered to a more realistic value of 8.0 feet. Also, a value of 0.0 feet for the standstill distance was determined to be unrealistic and so the minimum of the range was increased to 2.0 feet.

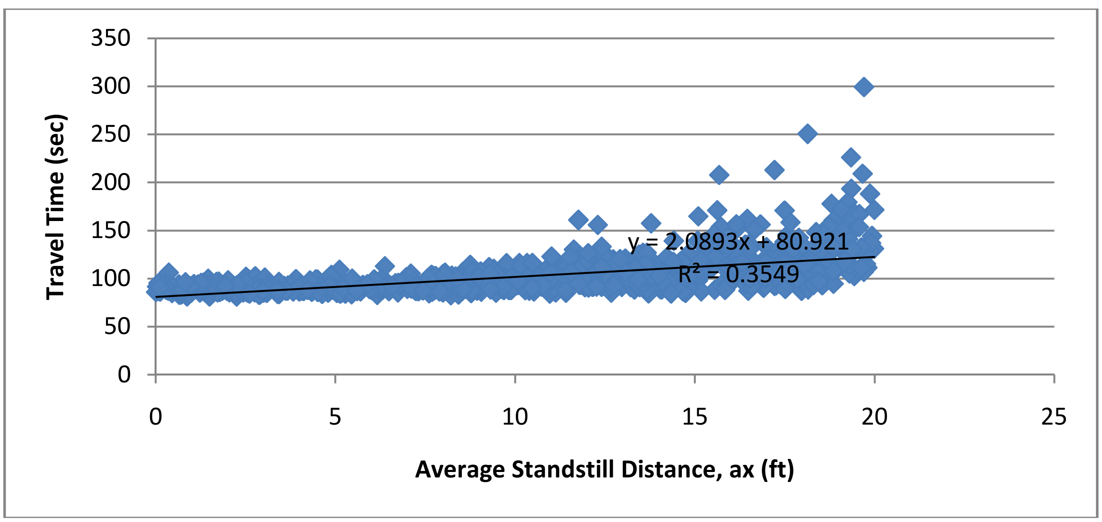


Figure 10: Average Travel Times on Segment #5 vs. the Average Standstill distance

Another reason for modifying parameter ranges is that certain values result in a significant number of reported errors that are not reflective of real-world observations. For example, the initial range for the waiting time before diffusion parameter was 20-80 seconds, but when the value was near 20 seconds the number of errors (i.e. vehicles being removed from the network) during the simulation increased dramatically. The range was modified to a more realistic waiting time range of 40-80 seconds.

The minimum look ahead distance range was narrowed not because of unrealistic values, but because the range was unnecessarily large. Due to the nature of this parameter (i.e. used when vehicle are place laterally within a lane) for the Cobb Parkway model its value is largely irrelevant. The range was thus narrowed to a more reasonable range of realistic values for a driver's minimum look ahead distance. The initial and final parameter ranges are shown in Table 6 below, empty values in the final range column indicates that the parameter was not changed.

Table 6: Initially Selected Parameter Ranges

#	Parameter	Initial Range	Final Range
1	Desired Speed Distribution Range	±0.0-10.0 mph	±0.5-10.0 mph
2	Look-ahead distance min	0-900 ft	0-300 ft
3	Look-ahead distance max	500-1000 ft	500-1200 ft
4	Number of observed vehicles	2-8	
5	Average standstill distance, ax	0.0-20.0 ft	2.0-8.0 ft
6	Additive part of safety distance, bx_{add}	0.0-8.0	0.0-3.0
7	Multiplicative part of safety distance, bx_{mult}	0.0-8.0	0.0-3.0
8	Maximum Deceleration (own)	-20.0 - -3.0 ft/s²	
9	Maximum Deceleration (trailing)	-20.0 - -3.0 ft/s²	
10	Accepted Deceleration (own)	-6.0 - -0.33 ft/s²	
11	Accepted Deceleration (trailing)	-6.0 - -0.33 ft/s²	
12	Reduction rate (own)	50-300	50-200
13	Reduction rate (trailing)	50-300	50-200
14	Waiting time before diffusion	20–80 sec	40–80 sec
15	Min. headway (front/rear)	1.64-25.00 ft	
16	Safety distance reduction factor	0.0-1.0	
17	Max. deceleration for cooperative braking	-35.0 - -3.0 ft/s²	
18	Reduction factor for changing lanes before a signal	0.3-0.9	
19	Start upstream of stop line	200–600 ft	
20	End downstream of stop line	200–600 ft	
21	Emergency stop distance	6.56–30.0 ft	
22	Lane change distance	300–1000 ft	500–1000 ft
23	Random seed value	1-999	

5.6 1st Parameter Set Results

The first parameter set includes the 22 parameters not eliminated during the first step of the procedure as well as an additional parameter for the simulation random seed value. The random seed value was added to allow for an exploration of the impact of randomness do to the inherent stochasticity included in the model. As described in the general procedure, 1,000 sets of random parameter values for the 23 parameters were created and then used to create 2,000 corresponding VISSIM input files, 1,000 for each volume case (i.e. 100% AM volumes and 75% AM volumes). The results from these simulations were then used to further examine which parameters should be included in the model calibration.

The results from the simulations are used to create scatter plots of the parameter values versus the travel times for each of the 23 parameters and 5 travel times. These scatter plots are then used to quantify the effect that a parameter has based on the percentage effect the parameter has on the mean of the travel times on each segment and a visual assessment of the impact on the variability. For this study it was determined that a 4% effect on the mean travel time of at least two segments was a reasonable significance threshold. However, other thresholds could certainty be considered and one area of future study is exploring the impact of the select threshold on method convergence.

5.6.1 100% Volume Results

Analyzing the results from the 100% volume runs led to the elimination of 11 parameters because they had a negligible effect on the travel time measurements. The final results from the analysis are shown in Table 7 and Table 8 below which list the selected and eliminated parameters and each parameter's percentage effect on the mean of the travel times on each travel time segment. The reasoning behind the decisions to keep or eliminate each variable is explained next.

Table 7: 1st Round 100% Volume Scenario, Parameter's Effect on the Mean of the Travel Times for Retained Parameters

		Travel Time Segment				
#	**Parameter**	**#1**	**#2**	**#3**	**#4**	**#5**
1	Desired Speed Distribution Range	-0.32%	1.58%	-0.18%	-0.59%	3.15%
5	Average standstill distance, ax	5.97%	7.62%	6.19%	8.44%	14.99%
6	Additive part of safety distance, bx_{add}	6.20%	19.28%	7.14%	2.59%	-5.61%
7	Multiplicative part of safety distance, bx_{mult}	4.45%	11.17%	4.86%	2.20%	-0.72%
8	Maximum Deceleration (own)	11.41%	1.15%	7.30%	-1.11%	-20.93%
9	Maximum Deceleration (trailing)	4.48%	-0.87%	2.60%	-0.87%	-7.94%
15	Min. headway (front/rear)	17.71%	4.27%	12.54%	-1.87%	-28.78%
16	Safety distance reduction factor	11.14%	-0.70%	7.28%	-1.85%	-20.61%
17	Max. deceleration for cooperative braking	7.85%	-1.82%	4.45%	-1.42%	-9.90%
18	Reduction factor for changing lanes before a signal	1.61%	14.61%	2.96%	0.32%	-0.08%
22	Lane change distance	-17.91%	-0.85%	-11.85%	1.45%	22.94%

Table 8: 1st Round 100% Volume Scenario, Parameter's Effect on the Mean of the Travel Times for Eliminated Parameters

		Travel Time Segment				
#	**Parameter**	**#1**	**#2**	**#3**	**#4**	**#5**
2	Look-ahead distance min	1.52%	-1.94%	0.86%	-1.26%	-6.73%
3	Look-ahead distance max	-2.31%	-0.39%	-1.42%	-0.05%	2.92%
4	Number of observed vehicles	-2.10%	0.52%	-0.68%	-0.15%	-0.72%
10	Accepted Deceleration (own)	1.91%	-0.37%	1.71%	0.45%	-2.31%
11	Accepted Deceleration (trailing)	1.38%	-2.50%	0.87%	0.40%	-1.90%
12	Reduction rate (own)	-2.84%	3.28%	-2.03%	-0.25%	5.56%
13	Reduction rate (trailing)	1.42%	2.10%	1.76%	0.34%	-0.24%
14	Waiting time before diffusion	2.06%	0.67%	1.65%	-0.24%	-3.68%
19	Start upstream of stop line	-0.41%	-3.24%	-0.47%	-2.15%	-5.38%
20	End downstream of stop line	-0.31%	-2.80%	-1.03%	0.40%	2.50%
21	Emergency stop distance	1.59%	4.25%	3.10%	0.30%	0.62%

Of the eleven parameters not eliminated eight showed a significant effect on three or more of the travel time segments. These parameters included the three car following model parameters, maximum deceleration (own) parameter, minimum headway parameter, safety distance reduction factor parameter, maximum deceleration for cooperative braking parameter, and the lane change distance parameter. These eight parameters showed the strongest effect on the travel times and were immediately selected for the next round of analysis. The figures below illustrate how it was clear that these parameters had an effect on the model. The first figure, Figure 12, is the scatter plot of the minimum headway parameter versus the average travel time on travel time segment #3 during each of the 1,000 runs. The plot shows a strong relationship between increasing travel times and increasing minimum headway values.

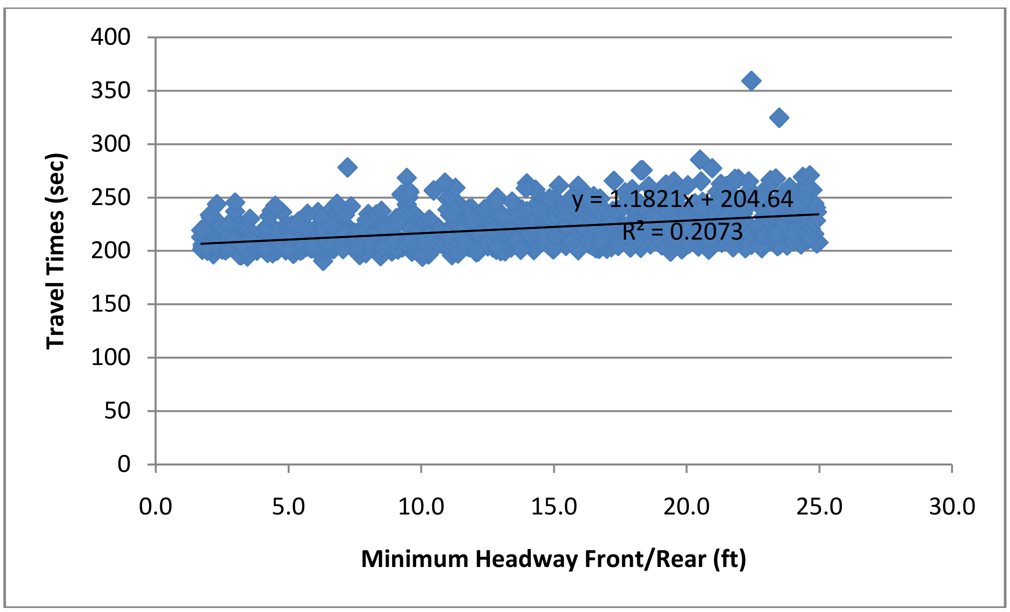


Figure 11: Average Travel Times on Segment #3 vs. the Minimum Headway

The second figure, Figure 12, shows the percent effect on the mean by the average standstill distance, Ax, for each of the five travel time segments. The average standstill distance effects the mean travel time by over 4% on all of the travel time segments and by near to or more than 8% on three of the segments. Similar results for the other six parameters can be found in the appendices.

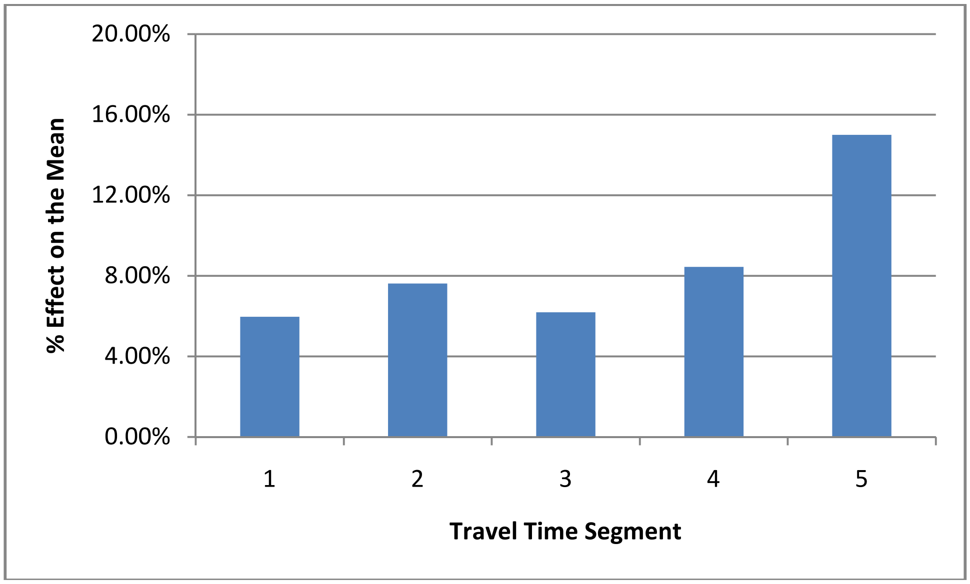


Figure 12: Average Standstill Distance Effect on the Mean Travel Time for each Segment

Two parameters, maximum deceleration (trailing) and reduction factor for changing lanes before a signal, did not have as significant an impact as the other parameters but still appeared to at least potentially have some impact. In Figure 13 it is clear that the maximum deceleration (trailing) parameter does not have as pronounced of an effect on the mean of the travel times for each segment as the previous selected parameters, but there is evidence of an effect seen on segments #1 and #5.

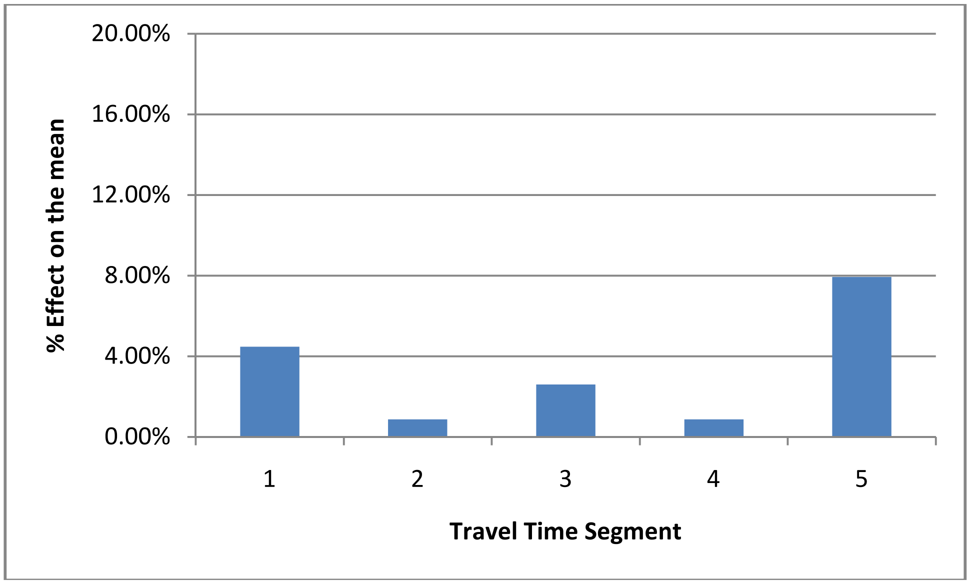


Figure 13: Maximum Deceleration (trailing) Effect on the Mean Travel Time for each Segment

The reduction factor for changing lanes before a signal parameter effect exceeds 4% for only one travel time route, thus it does not meet the set thresholds. However, for route #2 the effect was sufficiently large, at over 14% that it was decided to retain the parameter. Although, the associated scatter plot, see Figure 14, raises the concern that values for the parameter larger than 0.7 led to unrealistic results. This is potentially the underlying reason for the travel time impact seen on travel time route #2. For the next sets of runs the range for this parameter will be reduced from 0.3-0.9 to 0.3-0.7.

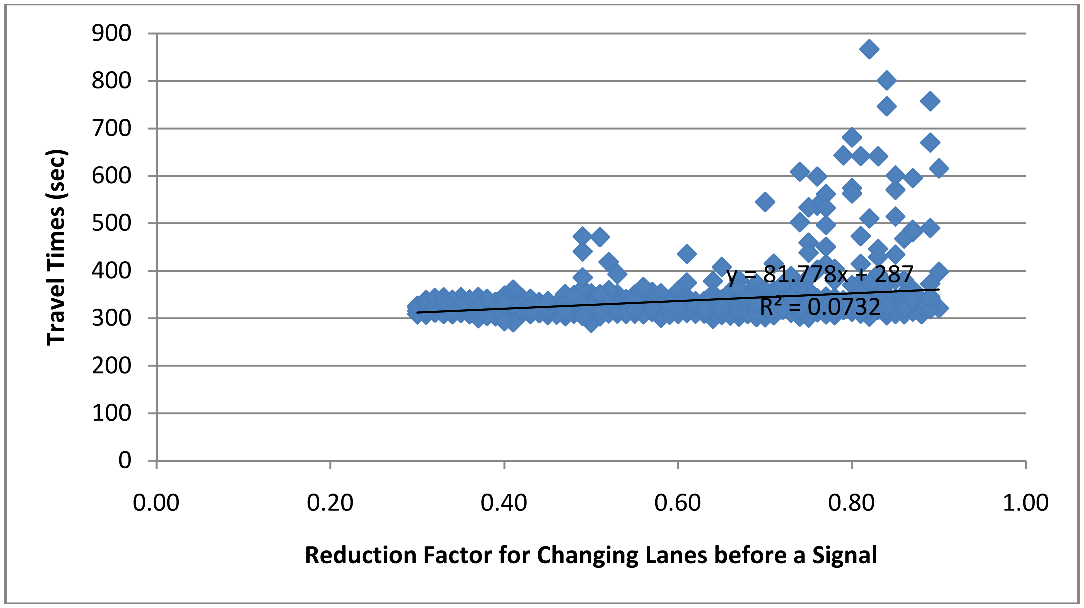


Figure 14: Average Travel Times on Segment #2 vs. Reduction Factor for Changing Lanes before a Signal

The last selected parameter was the desired speed distribution range. This parameter did not have a significant effect on any of the measured travel times, but was not eliminated given consistent results from previous studies and past analyst experience that this parameter can have a significant impact on the simulation results. It was decided to include this parameter in the next iteration to confirm its impact, or lack thereof, on the model.

All 11 of the eliminated parameters had no significant effect on the model. Figure 15 and Figure 16 are representative of the results seen for all 11 eliminated parameters on all 5 travel time segments. The scatter plots show a flat, horizontal distribution of travel times across all of the values of the parameter. The results therefore show very little effect on the mean travel time on any of the travel time segments.

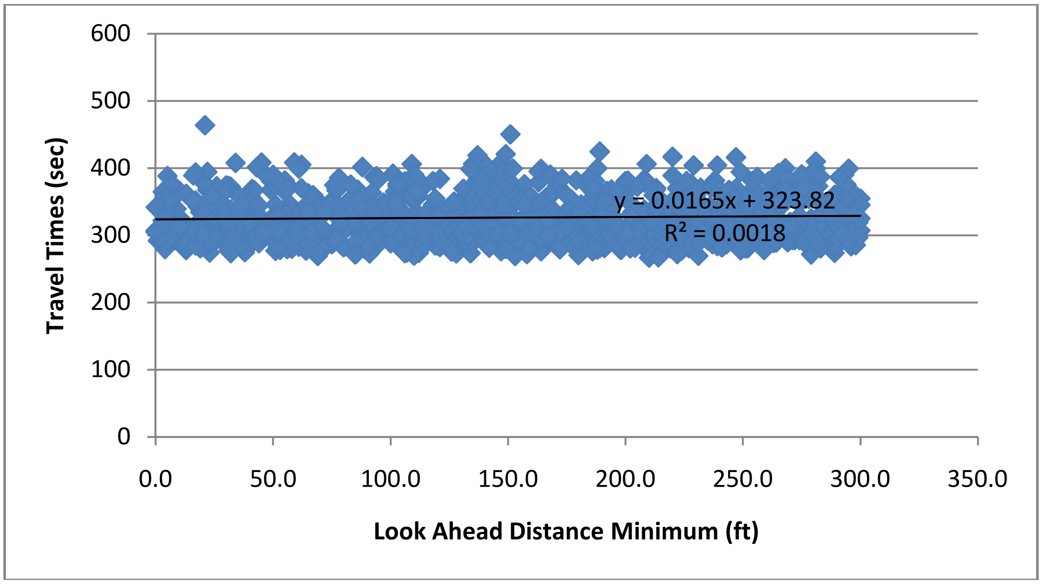


Figure 15: Average Travel Times on Segment #1 vs. the Look Ahead Distance Minimum

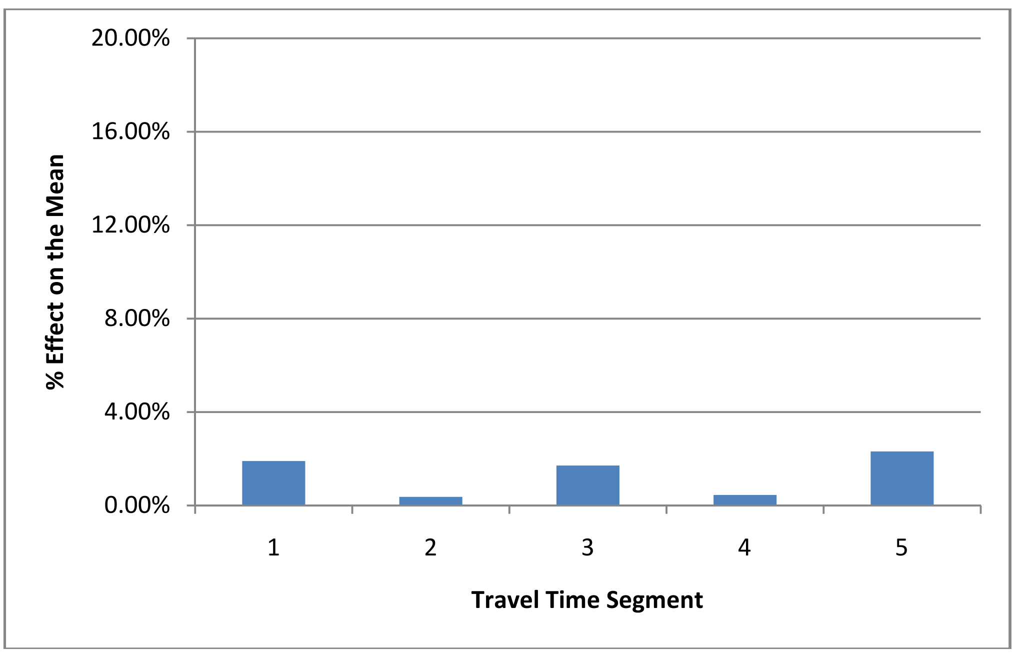


Figure 16: Accepted Deceleration (own) Effect on the Mean Travel Time for each Segment

5.6.2 75% Volume Results

The results from the 75% volume runs showed less significant impacts from the parameters than in the previous 100% case. This is most likely due to the difference in congestion between the two models. Many of the parameters being analyzed are directly related to vehicle to vehicle interactions which are much more common in a congested network than in an uncongested network.

None of the parameters were observed to have effects at the level of the eight most influential parameters from the 100% volume runs, but out of the nine that had at least some noticeable effect in the 100% volume runs six also had at least a minimal effect, at or near the 4% level, in the 75% volume runs. These six parameters included the average standstill distance, additive part of safety distance, maximum deceleration (own), minimum headway, safety distance reduction factor, and lane change distance. An example of the results is given below in Figure 17.

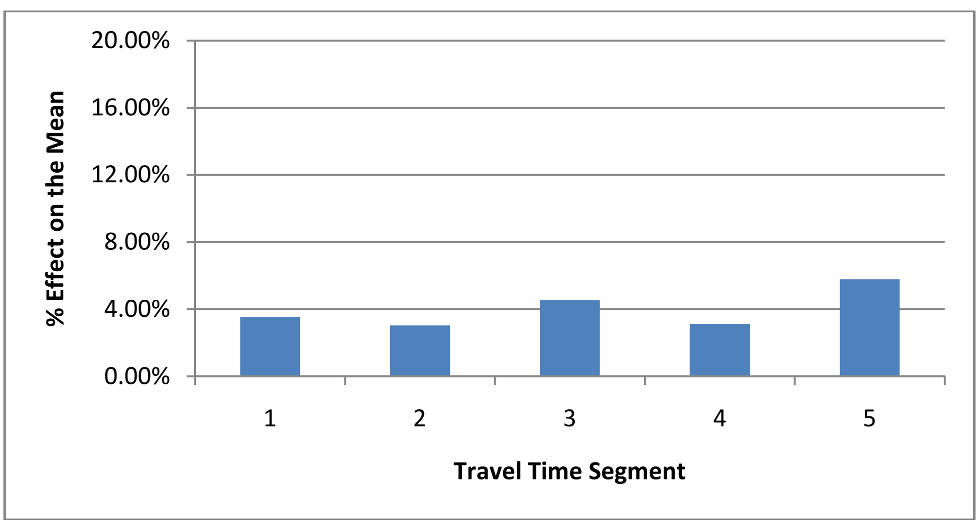


Figure 17: Additive Part of Safety Distance Effect on the Mean Travel Time for each Segment

The four parameters that were significant in the 100% volume runs but not in the 75% volume runs were the multiplicative part of safety distance, the maximum deceleration (trailing), the maximum deceleration for cooperative braking, and the reduction factor for changing lanes before a signal. However, for this initial iteration the multiplicative part of safety distance parameter, maximum deceleration for cooperative braking parameter for lane changes, and the reduction factor for changing lanes before a signal were not eliminated given their the perceived impacts in the 100% scenario and previous analyst experience. Thus, it was decided to retain these variables for at least one additional iteration. The maximum deceleration (trailing) parameter for lane changes was eliminated and was the only parameter eliminated for the 75% volume runs that was not eliminated for the full volume runs.

The eleven parameters that were eliminated after the full volume runs were also eliminated after these runs since they again had insignificant effects on the travel time results. Also, the desired speed distribution range parameter was not eliminated for the same reasons discussed in the previous section.

The final results from the 75% volume analysis are shown in Table 9 and Table 10 below which lists the selected and eliminated parameters.

Table 9: 1st Round 75% Volume Scenario, Parameter's Effect on the Mean of the Travel Times for Retained Parameters

		Travel Time Segment				
#	Parameter	#1	#2	#3	#4	#5
1	Desired Speed Distribution Range	0.20%	1.58%	0.51%	-0.10%	2.63%
5	Average standstill distance, ax	3.01%	1.52%	3.09%	3.91%	20.55%
6	Additive part of safety distance, bx_{add}	3.55%	3.03%	4.55%	3.12%	-5.78%
7	Multiplicative part of safety distance, bx_{mult}	2.09%	1.57%	2.52%	2.13%	-0.47%
8	Maximum Deceleration (own)	5.43%	1.12%	2.67%	2.97%	-6.71%
15	Min. headway (front/rear)	7.23%	0.92%	3.08%	1.69%	-15.72%
16	Safety distance reduction factor	5.10%	0.58%	2.18%	1.16%	-6.04%
17	Max. deceleration for cooperative braking	3.15%	-0.33%	0.57%	-0.37%	-8.51%
18	Reduction factor for changing lanes before a signal	1.84%	2.13%	2.93%	1.67%	0.41%
22	Lane change distance	-7.49%	0.09%	-2.69%	0.64%	10.46%

Table 10: 1st Round 75% Volume Scenario, Parameter's Effect on the Mean of the Travel Times for Eliminated Parameters

		Travel Time Segment				
#	Parameter	#1	#2	#3	#4	#5
2	Look-ahead distance min	0.89%	-0.10%	0.09%	-0.25%	-0.87%
3	Look-ahead distance max	-0.88%	-0.31%	-0.35%	-0.26%	2.84%
4	Number of observed vehicles	-0.61%	-0.12%	0.10%	-0.32%	-2.67%
9	Maximum Deceleration (trailing)	3.01%	0.25%	0.92%	0.94%	-4.21%
10	Accepted Deceleration (own)	1.36%	0.19%	0.71%	0.72%	0.11%
11	Accepted Deceleration (trailing)	0.16%	-0.40%	-0.18%	-0.01%	0.13%
12	Reduction rate (own)	-1.15%	0.02%	-0.11%	-0.25%	-1.06%
13	Reduction rate (trailing)	0.80%	0.38%	0.63%	1.24%	0.13%
14	Waiting time before diffusion	0.24%	0.30%	0.21%	0.71%	0.20%
19	Start upstream of stop line	-0.04%	-0.35%	-0.27%	-0.90%	-1.96%
20	End downstream of stop line	-0.11%	-0.38%	-0.41%	0.06%	0.83%
21	Emergency stop distance	1.22%	0.41%	1.37%	0.34%	1.70%

5.7 2^{nd} Parameter Set Results

5.7.1 Comparison to the 1^{st} Parameter Set Results

The second parameter set includes the 11 selected parameters for the 100% volume case and the 10 selected parameters for the 75% volume case. For those parameters that were eliminated in the first iteration the calibrated values from the initial model are used. As previously, the random seed value is also included as an additional parameter. The results from the 2^{nd} parameter set runs are analyzed in a manner similar to that of previous results. In addition, general comparisons were made between the results of the simulations from the first and second procedure iterations. If the results from the new runs produce much lower or higher travel time measurements than the previous runs it would indicate that one or more of the eliminated parameters did have an unseen effect on the model's results. In Figure 18 and Figure 19 the average travel times for all 1,000 runs from each travel time segment are compared for both parameter sets. The similarity between these results helps support the first iteration parameter eliminations.

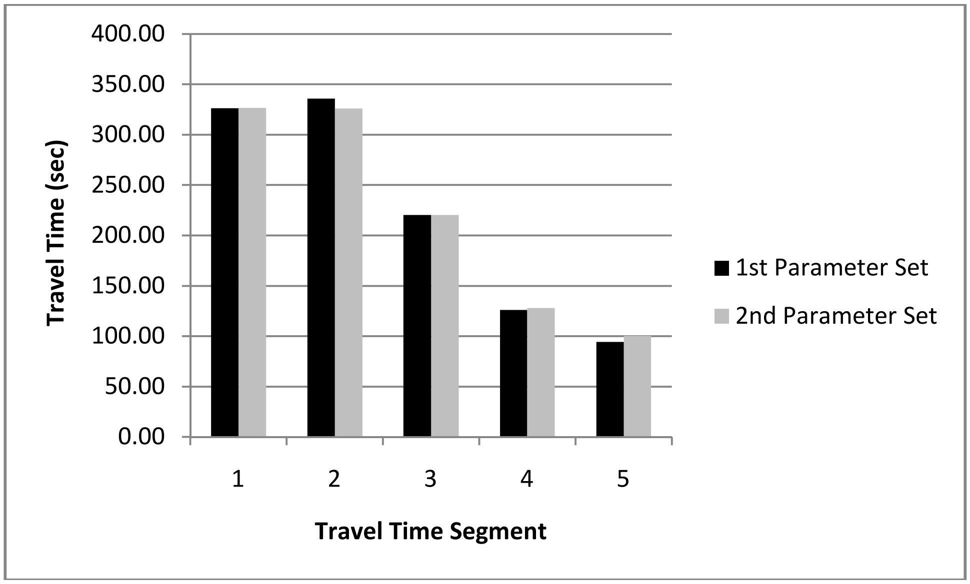


Figure 18: 100% Volume Comparison of Average Travel Times from the 1st and 2nd Parameter Set Runs

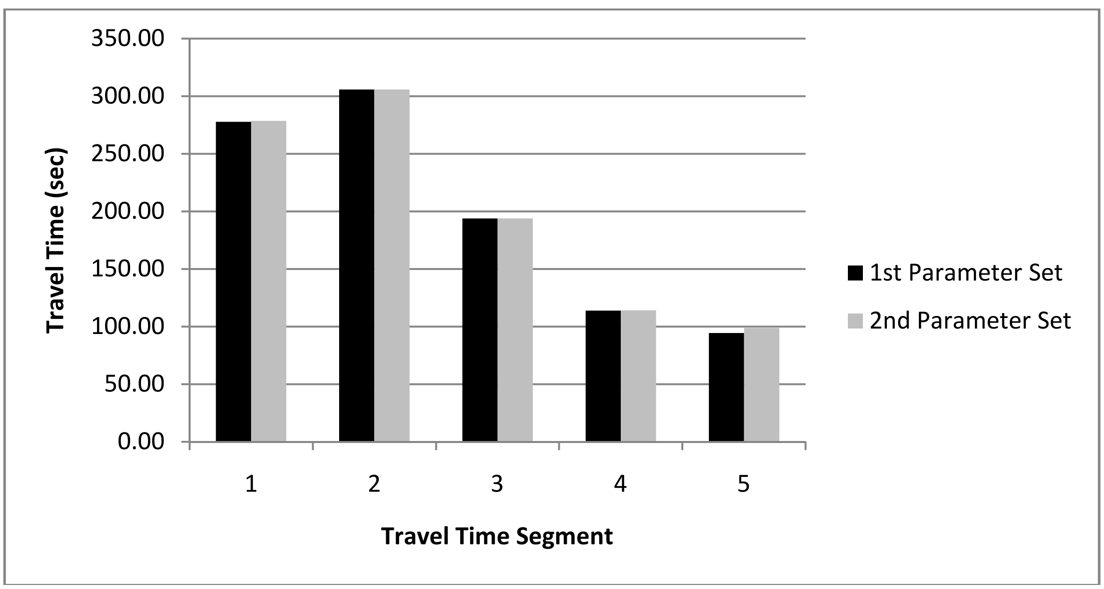


Figure 19: 75% Volume Comparison of Average Travel Times from the 1st and 2nd Parameter Set Runs

It is noted that a potentially significant difference was observed on segments #2 and #5. The reduction in travel times on segment #2 in the 100% volume case was due to the narrowed range of the reduction factor for changing lanes before a signal. The new more realistic range eliminated many of the unrealistic outlying travel time values and lowered the overall average travel time by 10 seconds. Segment #5 as previously discussed, is subject to increased variability. Also, the conditions downstream of the segment can cause the segment to become even more congested due to congestion spillback. This is highlighted in Figure 20. Thus, the difference between iteration 1 and iteration 2 on segment five are likely well within the bounds of significance.

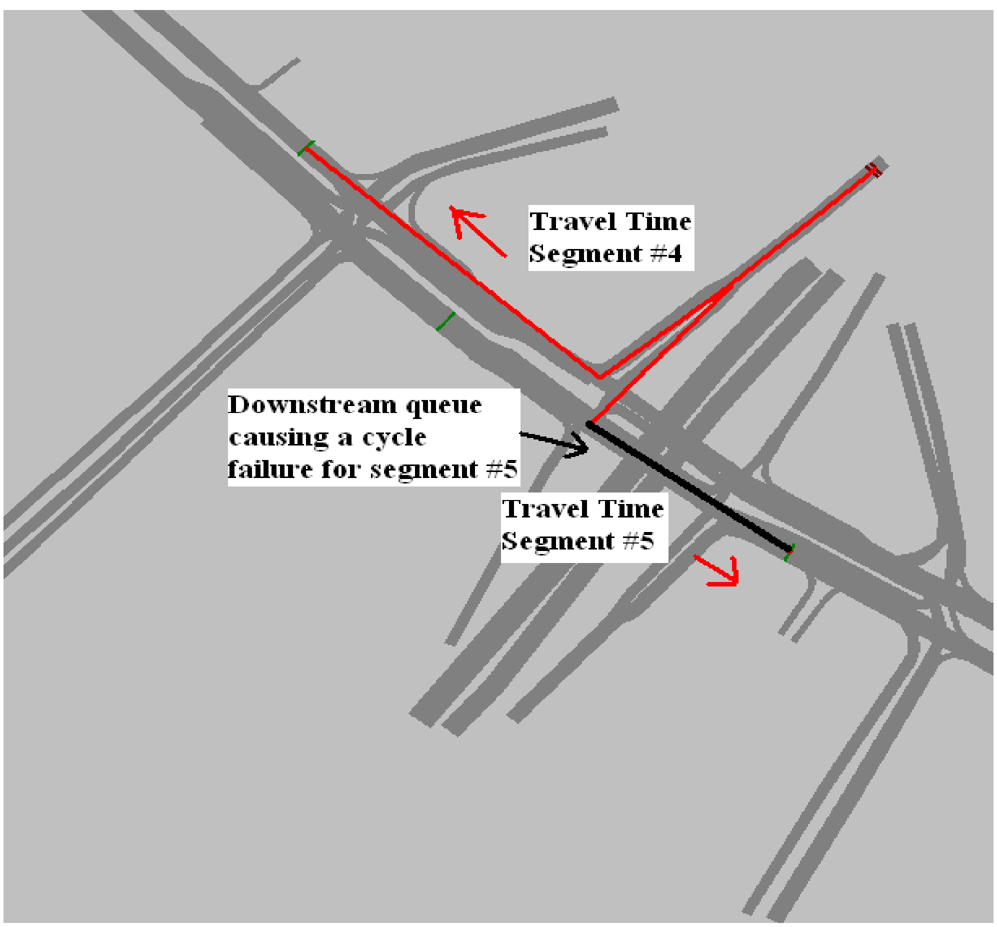


Figure 20: Queue Downstream of Travel Time Segment #5 Blocking Traffic

However, the spillback impacting travel route #5 does highlight an interesting parameter effect. Interestingly, for travel time route #5 there is an inverse relationship between the minimum headway parameter and the travel time than that seen on the other travel time routes. This is illustrated in Figure 21 with the scatter plots of the minimum headway parameter versus the average travel times on segment #1 and segment #5 for the 100% volume scenario, iteration #2. When the vehicles on Cobb Parkway experience less congestion (represented by Travel Time Route #1) they have a tendency to more often fill the space on Cobb Parkway required for vehicles tuning onto the Cobb Parkway from I-285 (Travel Time route #5). When the vehicles on Travel Time Route #1 experience congested conditions (bottlenecks) upstream of this point they arrive at segment #5 in reduced volumes, resulting in less congestion interference being experience by those vehicles on Travel Time Route #5. This behavior can be observed during the simulation runs very clearly.

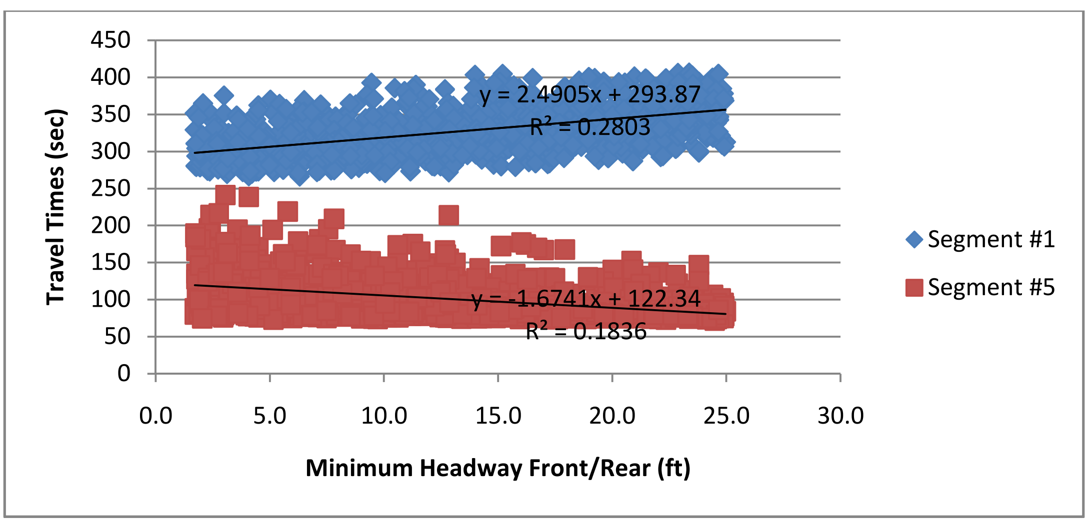


Figure 21: Relationship between the Minimum Headway and Travel Times on Travel Time Route #1 and the Minimum Headway and Travel Times on Travel Time Route #5 for 100% Volume Scenario of Iteration #2.

5.7.2 100% Volume Results

As expected the eight parameters that had a strong effect on the mean travel times for the first parameter set runs showed similar results for the second parameter set runs. Once again these eight parameters were selected for the next round of analysis. The reduction factor for changing lanes before a signal parameter was eliminated. After narrowing the parameter's range its effect on the average travel time on segment #2 was eliminated.

The desired speed distribution range parameter again showed no effect on the travel times recorded during the simulations. As this result continued to be counterintuitive additional experiments were run to understand this finding. The hypothesis for why the parameter was insignificant was that the average desired speed of 45 mph on the network was such that vehicles reached a traffic signal or the back of a queue before they reached their desired speed. Therefore, vehicles were unable able to reach their respective desired speeds, greatly reducing its significance.

In order to test this hypothesis the runs were completed again using the 100% volume scenario, iteration #2 parameter set, but the average desired speed was lowered from 45 mph to 30 mph allowing for minimum and maximum desired speeds of 20 mph and 40 mph respectively. The results showed that for all three of the long travel time segments the desired speed distribution range was one of the most influential parameters. These results support the hypothesis that the combination of the signal spacing and high average desired speed are rendering the desired speed distribution range insignificant to the model's results. Because of these results it was also logical to eliminate this parameter for this modeling effort. However, as a general rule any elimination of this parameter should be checked in a similar manner. The final selected and eliminated parameters are displayed below in Table 11 and Table 12 along with selected results from the 30 mph average speed experiment in Figure 22 and Figure 23.

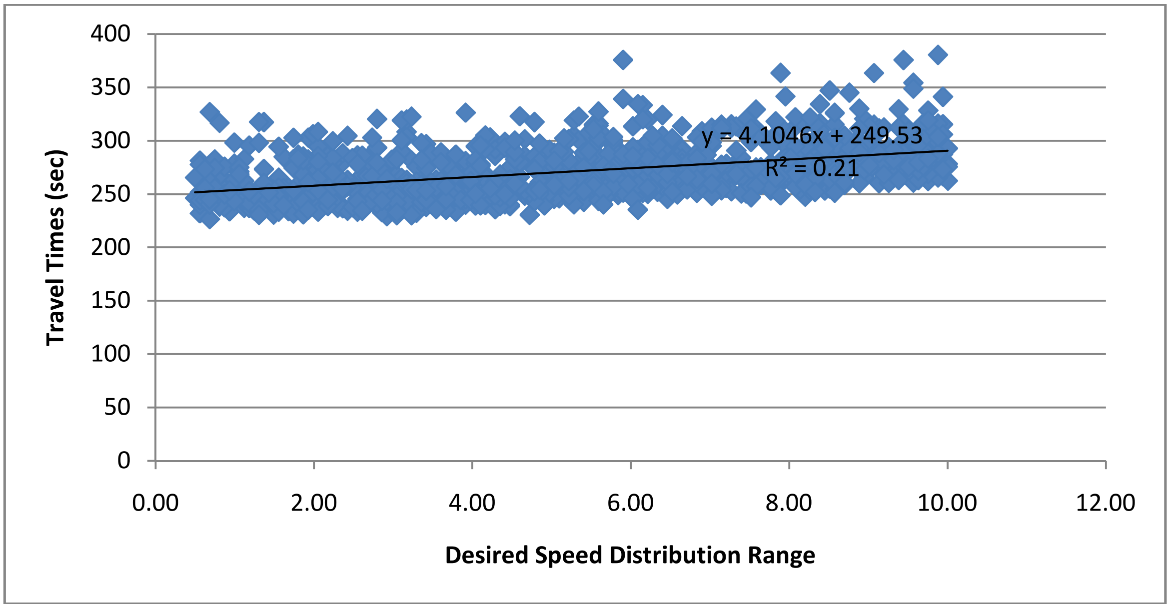


Figure 22: Average Travel Times on Segment #3 vs. the Desired Speed Distribution Range (30 mph trial)

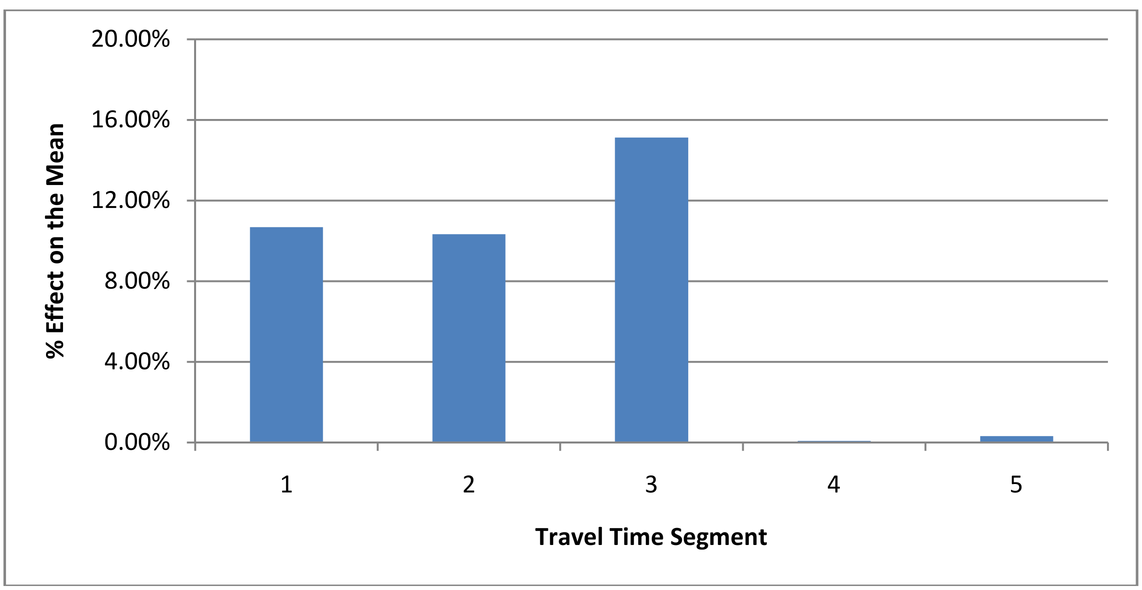


Figure 23: Desired Speed Distribution Range Effect on the Mean Travel time for each Segment (30 mph trial)

Table 11: 2nd Round 100% Volume Scenario, Parameter's Effect on the Mean of the Travel Times for Retained Parameters

#	Parameter	Travel Time Segment				
		#1	#2	#3	#4	#5
5	Average standstill distance, ax	5.98%	4.47%	6.46%	10.78%	13.95%
6	Additive part of safety distance, bx_{add}	5.02%	6.99%	5.81%	2.71%	-9.68%
7	Multiplicative part of safety distance, bx_{mult}	3.21%	3.74%	3.54%	1.20%	-5.68%
8	Maximum Deceleration (own)	9.63%	1.98%	6.77%	-0.63%	-20.74%
9	Maximum Deceleration (trailing)	5.22%	1.16%	3.69%	-2.35%	-12.01%
15	Min. headway (front/rear)	17.73%	4.50%	13.16%	-4.84%	-39.03%
16	Safety distance reduction factor	9.86%	1.46%	6.72%	-2.42%	-24.10%
17	Max. deceleration for cooperative braking	8.40%	1.30%	5.51%	-2.40%	-14.97%
22	Lane change distance	-16.96%	-1.98%	-12.27%	4.54%	32.24%

Table 12: 2nd Round 100% Volume Scenario, Parameter's Effect on the Mean of the Travel Times for Eliminated Parameters

#	Parameter	Travel Time Segment				
		#1	#2	#3	#4	#5
1	Desired Speed Distribution Range	-0.47%	1.50%	-0.40%	-0.60%	4.49%
18	Reduction factor for changing lanes before a signal	2.58%	3.74%	2.11%	-0.13%	-4.59%

5.7.3 75% Volume Results

The results from the 75% volume results mirrored the results from the full volume runs, but again the effects of the parameters were much less significant. The desired speed distribution range parameter was eliminated for the same reasons as in the 100% volume runs. The reduction factor for changing lanes before a signal parameter was also eliminated for the same reasons as in the 100% volume runs. The results are shown in Table 13 and Table 14.

Table 13: 2nd Round 75% Volume Scenario, Parameter's Effect on the Mean of the Travel Times for Retained Parameters

		Travel Time Segment				
#	Parameter	#1	#2	#3	#4	#5
5	Average standstill distance, ax	3.25%	1.67%	3.38%	4.79%	27.12%
6	Additive part of safety distance, bx_{add}	3.50%	3.29%	4.58%	3.12%	-4.95%
7	Multiplicative part of safety distance, bx_{mult}	1.77%	1.85%	2.32%	1.77%	-1.06%
8	Maximum Deceleration (own)	5.12%	1.09%	2.64%	3.39%	-9.13%
15	Min. headway (front/rear)	7.56%	0.68%	3.47%	2.11%	-14.54%
16	Safety distance reduction factor	5.06%	0.70%	2.25%	1.52%	-7.98%
17	Max. deceleration for cooperative braking	3.44%	-0.38%	0.45%	-0.39%	-6.50%
22	Lane change distance	-8.19%	-0.20%	-2.80%	0.72%	8.17%

Table 14: 2nd Round 100% Volume Scenario, Parameter's Effect on the Mean of the Travel Times for Eliminated Parameters

		Travel Time Segment				
#	Parameter	#1	#2	#3	#4	#5
1	Desired Speed Distribution Range	0.30%	1.81%	0.35%	-0.33%	2.29%
18	Reduction factor for changing lanes before a signal	1.82%	2.33%	2.68%	1.59%	-3.94%

5.8 3rd Parameter Set Results

5.8.1 Comparison to 1st Parameter Set Results

The third parameter set includes the nine remaining parameters for the 100% volume case and the eight remaining parameters for the 75% volume case. As in iteration 1 and iteration 2 the random seed value is also included as an additional parameter. The results from the third parameter set runs are also be compared to the results from the first and second parameter set runs to help confirm that the newly eliminated parameters did not have an influence on the model. Figure 24 and Figure 25 below show the average travel times on each segment from the third parameter set runs compared to the average travel times on each segment from the first and second parameter set runs. As stated previously the travel times on segment #2 are lower for the second and third parameter set runs due the range for the parameter reduction factor for changing lanes before a signal being narrowed from 0.3-0.9 to 0.3-0.7.

Overall, the results from the third iteration are very similar to the iteration one and two results. The average travel times for the long travel time segments are all within 0.5% of the first and second parameter set results except for segment #2, as explained previously. The results from the second and third parameter set runs for segment #2 are within 0.5% of each other. The results for travel time segment #4 are also very close, all results within 1.0% of each other. The average travel times on segment #5 did change by almost 5% between the first and third parameter set runs, but as discussed previously in this study the characteristics of segment #5 make it less consistent and more likely to produce variable results like those observed.

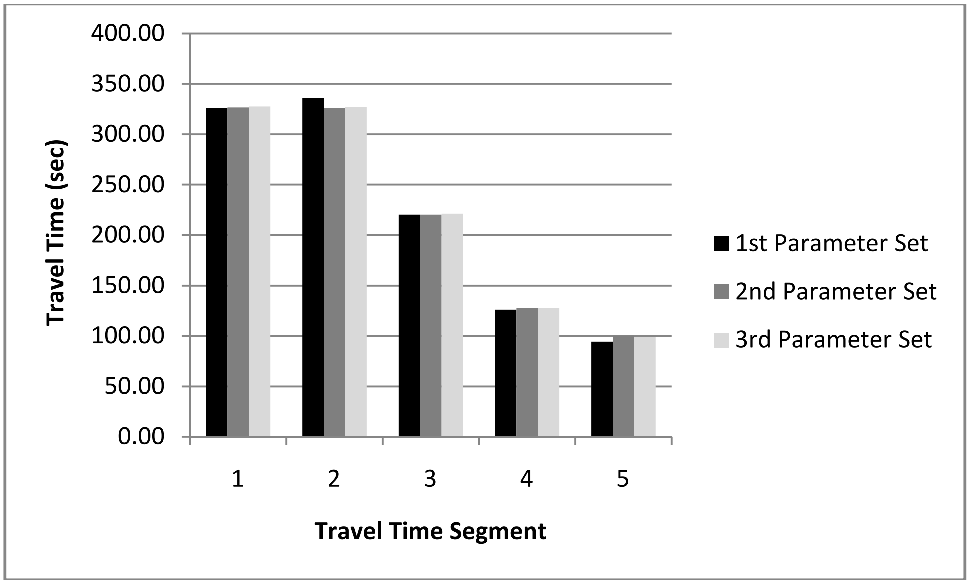


Figure 24: 100% Volume Comparison of Average Travel Times from the 1st, 2nd and 3rd Parameter Set Runs

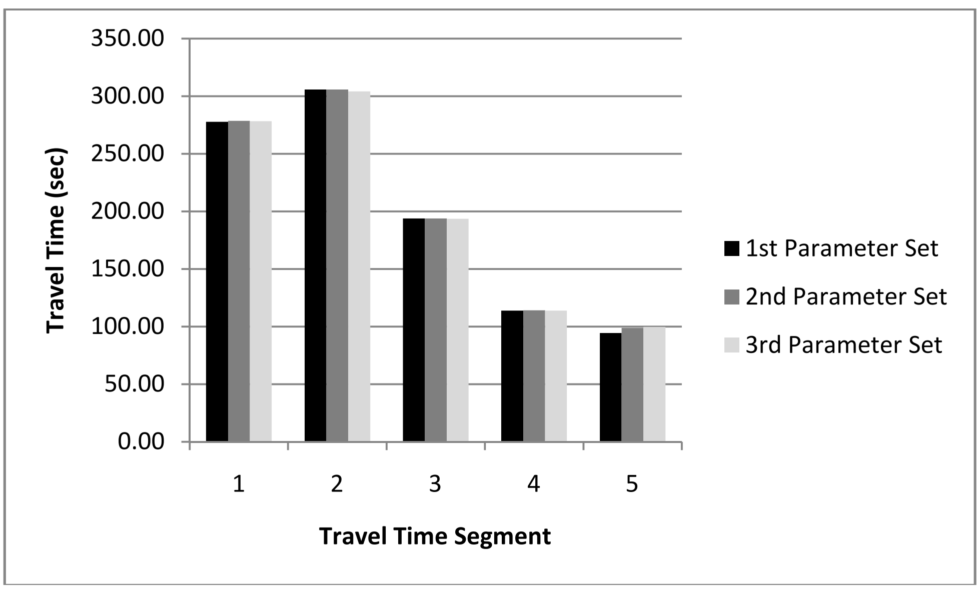


Figure 25: 75% Volume Comparison of Average Travel Times from the 1st, 2nd and 3rd Parameter Set Runs

5.8.2 100% Volume Results

The third parameter set runs produced results that confirmed that all nine of the remaining parameters have a significant effect on the measured travel times given the set thresholds. It would be inadvisable to eliminate any of the remaining parameters. Table 15 shows the percent effect on the mean of the average travel times on all of the segments for all parameters. These results confirm that this is the final set of parameters that should be considered for calibration.

Table 15: Final 100% Volume Scenario, Parameter's Effect on the Mean of the Travel Times for Retained Parameters

		Travel Time Segment				
#	**Parameter**	**#1**	**#2**	**#3**	**#4**	**#5**
5	Average standstill distance, ax	6.25%	5.74%	6.54%	9.19%	11.11%
6	Additive part of safety distance, bx_{add}	4.95%	10.46%	5.62%	1.65%	-11.67%
7	Multiplicative part of safety distance, bx_{mult}	3.80%	6.47%	4.32%	1.15%	-4.96%
8	Maximum Deceleration (own)	9.86%	1.29%	7.00%	-2.08%	-24.32%
9	Maximum Deceleration (trailing)	5.54%	1.09%	3.78%	-1.75%	-10.37%
15	Min. headway (front/rear)	17.50%	4.85%	13.10%	-5.69%	-40.46%
16	Safety distance reduction factor	10.57%	2.39%	7.22%	-4.96%	-28.45%
17	Max. deceleration for cooperative braking	8.59%	0.66%	5.48%	-2.85%	-15.16%
22	Lane change distance	-16.61%	-0.53%	-12.14%	4.60%	32.19%

5.8.3 75% Volume Results

The results for the 75% volume runs are similar but again show less significance regarding each parameter. While these eight parameters are the final set that should be considered for calibration, the results show that because the network is uncongested the input parameters will have less of an effect on the model and the actual network construction in

VISSIM is far more important than the calibration in making an effective model. The results and final selected parameters are shown in Table 16.

Table 16: Final 75% Volume Scenario, Parameter's Effect on the Mean of the Travel Times for Retained Parameters

		Travel Time Segment				
#	**Parameter**	**#1**	**#2**	**#3**	**#4**	**#5**
5	Average standstill distance, ax	2.94%	1.89%	3.47%	4.75%	27.08%
6	Additive part of safety distance, bx_{add}	3.34%	3.49%	4.65%	3.38%	-3.11%
7	Multiplicative part of safety distance, bx_{mult}	2.30%	2.00%	2.87%	2.41%	-0.25%
8	Maximum Deceleration (own)	4.75%	0.77%	2.50%	3.45%	-10.24%
15	Min. headway (front/rear)	8.09%	1.01%	3.86%	1.88%	-18.11%
16	Safety distance reduction factor	4.75%	0.26%	2.26%	1.04%	-9.70%
17	Max. deceleration for cooperative braking	3.90%	0.33%	0.91%	0.25%	-8.84%
22	Lane change distance	-7.25%	-0.36%	-3.03%	0.20%	9.63%

5.9 Conclusions

At the end of the procedure nine parameters were selected for the 100% volume case and eight for the 75% volume case. For both of these cases it was seen that only a few of these parameters affect the measured travel times by more than 10%. The Cobb Parkway network signalization tends to dominate the simulation performance, limiting the impact of the parameter calibration. That is, regardless of how the driver's behave they must always stop when the light is red. One of the biggest effects a parameter can have is in determining if more or fewer vehicles are able to make it through each green light.

The other factor affecting the results was the level of congestion. The parameters that had the largest effect in both cases were the minimum headway, safety distance reduction factor, and the lane change distance. All three of these parameter are concerned directly with the driver's decisions on when and how aggressively to change lanes. These parameters likely had the greatest effect because often vehicles would be queued or attempting to change lanes at the last possible moment. When these parameters were set such that drivers attempted to change lanes as early and aggressively as possible the congestion and travel times were minimized. Conversely, when driver's changed lanes later or less aggressively congestion spread throughout the network resulting in longer travel times. This also helps the understanding of why the parameters had less of an influence in the uncongested case. In the uncongested case, regardless of how drivers decided to change lanes the network rarely broke down due to congestion, so the results were less affected.

The procedure was effective in determining which parameters had a significant effect on the model. However, ultimately it appears that the construction of the model itself is more significant than the parameter values. The calibration of the parameters should be used to fine tune a model, but the results using the default parameter values must already be close to the values from the field data in order for the calibration to be successful. This means that accurately depicting how the actual roads can be converted into links and connectors and ensuring that data such as the average speed of vehicles on the network is known and reflected in the model is the most important step in creating a useful model.

The results from the procedure also show key differences from previous studies. In the previous studies seven parameters were used for calibration that were shown to be insignificant at least for the Cobb Parkway model. These seven parameters were:

1. Waiting time before diffusion
2. Emergency stop distance
3. Number of observed preceding vehicles
4. Accepted Deceleration (own)

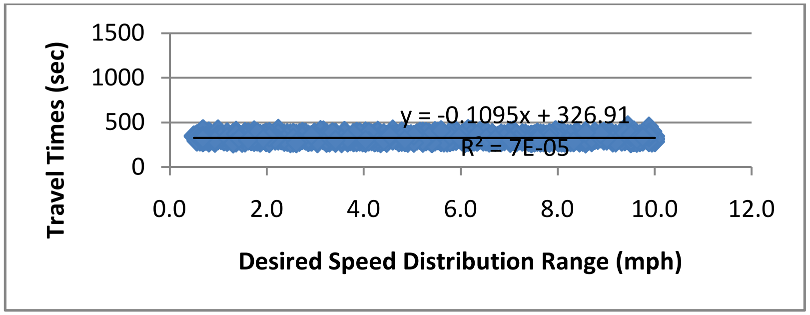
5. Accepted Deceleration (trailing)
6. Reduction rate (own)
7. Reduction rate (trailing)

These parameters were included in the previous studies because it is logical to assume they would be significant, but this study shows that for some models they are not. However, none of the previous studies excluded any of the parameters that were shown to be important for the Cobb Parkway model. These results demonstrate why determining which parameters to use for calibration is important. It is possible that arbitrary values were assigned to insignificant parameters that were used for model calibration.

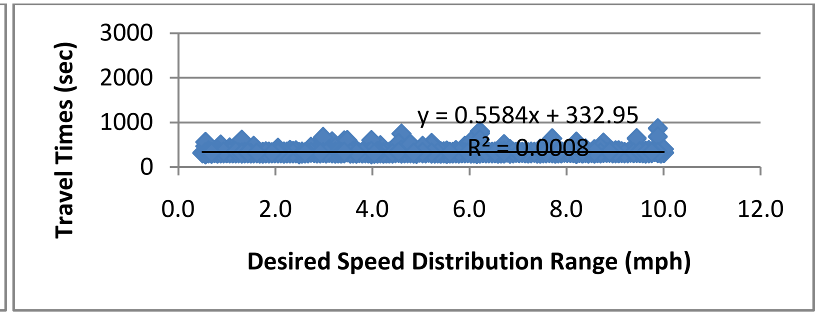
This procedure has been shown to be useful and successful at determining which parameters should be used for calibration. This type of study should be done before any model is calibrated, but it is also important not to rely on calibration to correct for mistakes made in the underlying model construction. While this procedure was tested on a heavily signalized urban arterial it may be even more useful in freeway applications where parameters affecting lane changes and car following are anticipated to have more of an effect on the results.

APPENDIX A

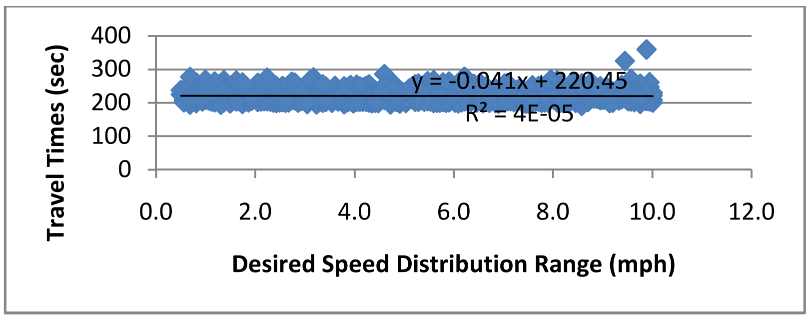
100% VOLUME SCENARIO RESULTS



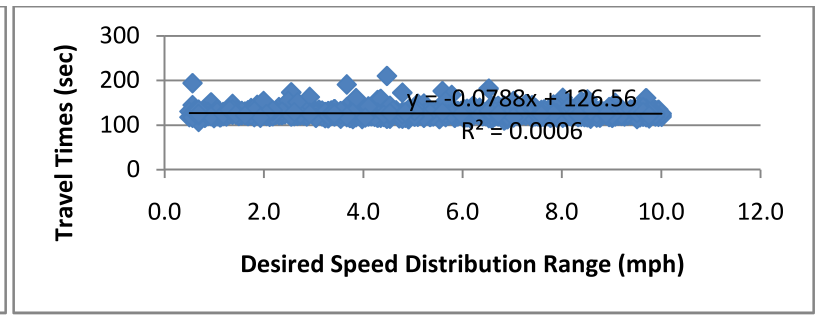
(a) Travel Time Segment #1



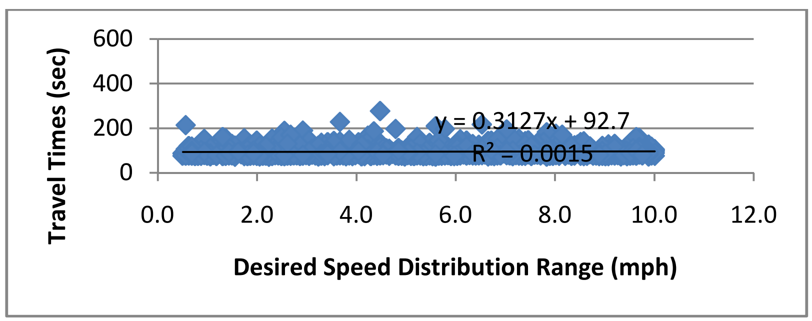
(b) Travel Time Segment #2



(c) Travel Time Segment #3

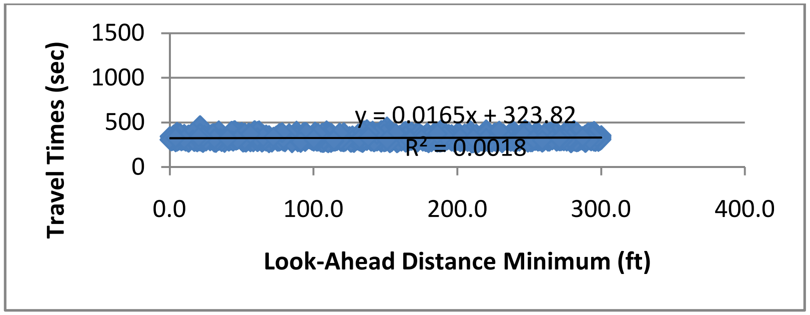


(d) Travel Time Segment #4

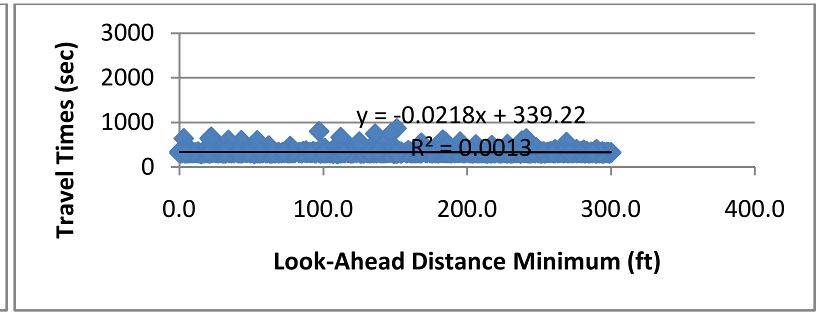


(e) Travel Time Segment #5

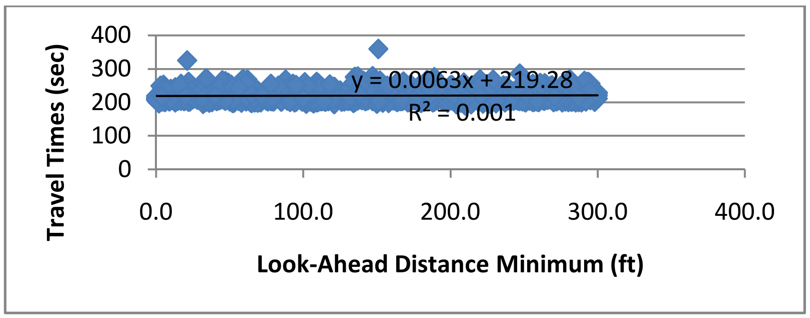
Figure 26(a-e): 100% Volume Scenario, Iteration #1, Parameter #1 Scatter Plots



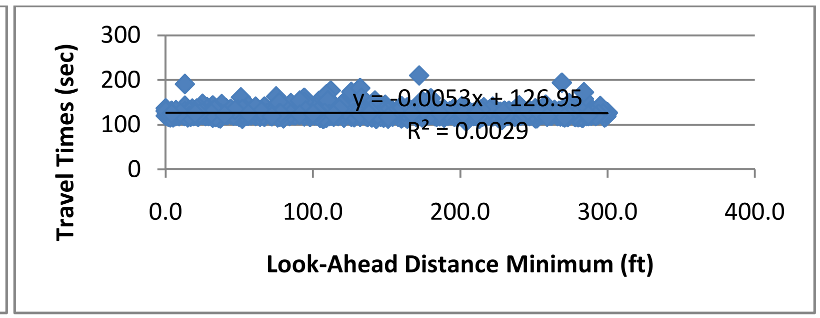
(a) Travel Time Segment #1



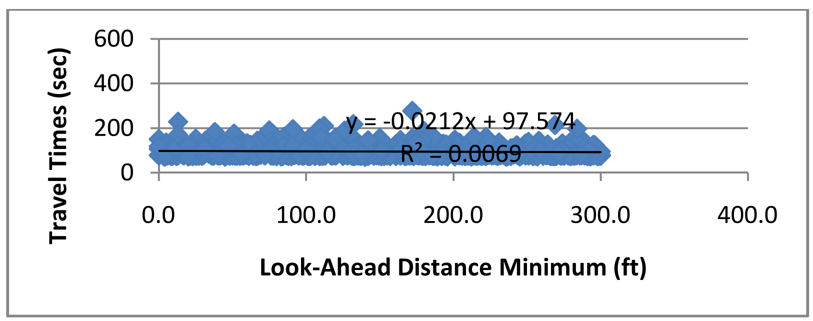
(b) Travel Time Segment #2



(c) Travel Time Segment #3

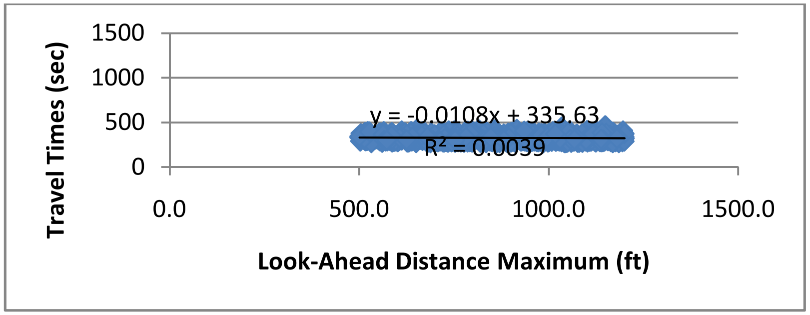


(d) Travel Time Segment #4

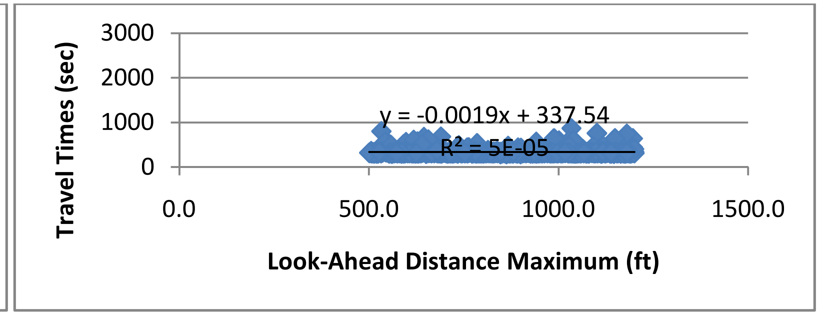


(e) Travel Time Segment #5

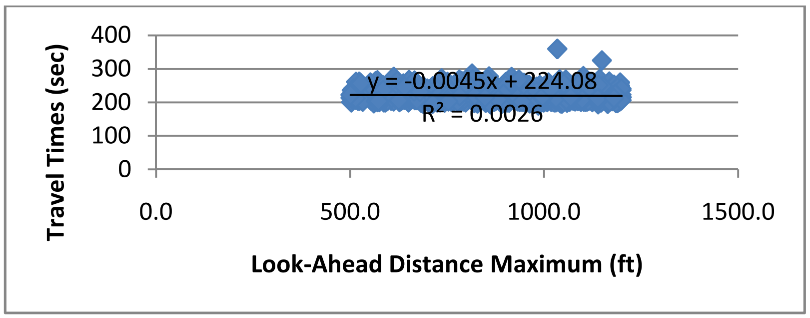
Figure 27(a-e): 100% Volume Scenario, Iteration #1, Parameter #2 Scatter Plots



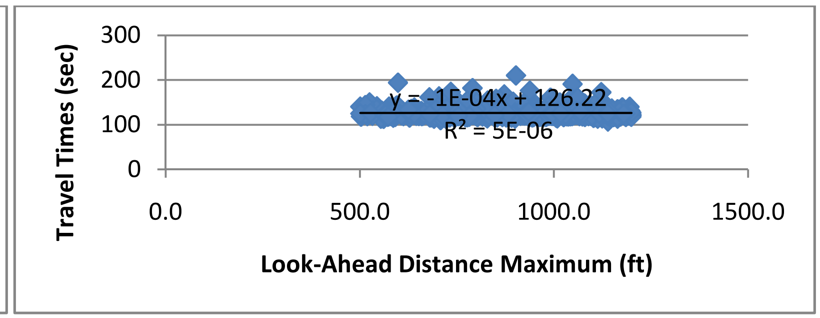
(a) Travel Time Segment #1



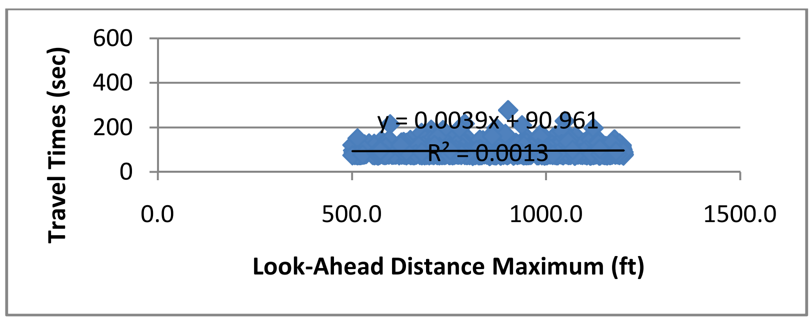
(b) Travel Time Segment #2



(c) Travel Time Segment #3

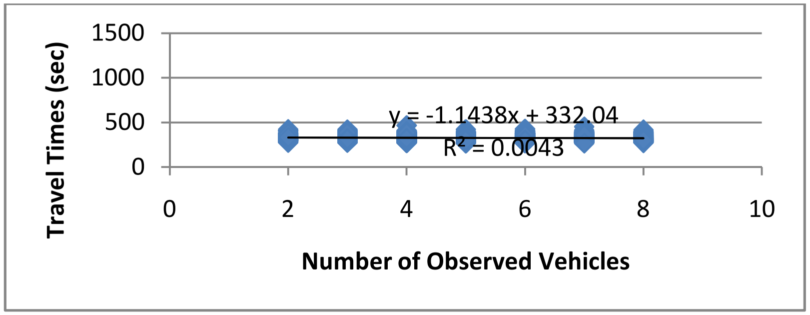


(d) Travel Time Segment #4

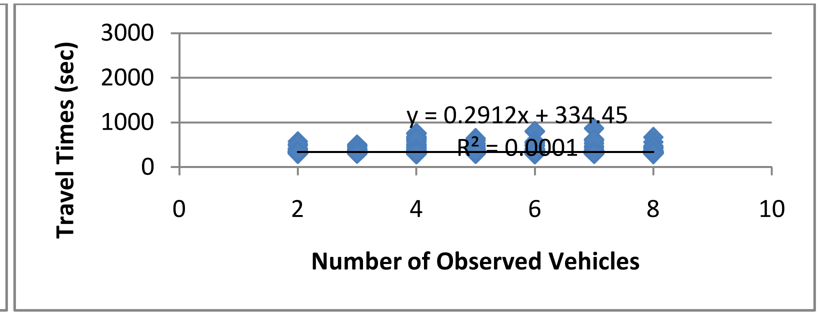


(e) Travel Time Segment #5

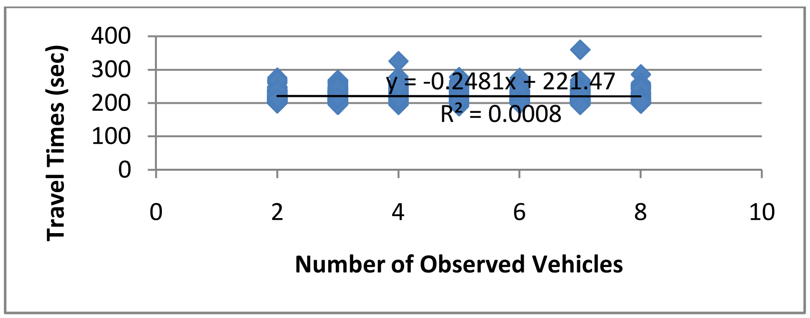
Figure 28(a-e): 100% Volume Scenario, Iteration #1, Parameter #3 Scatter Plots



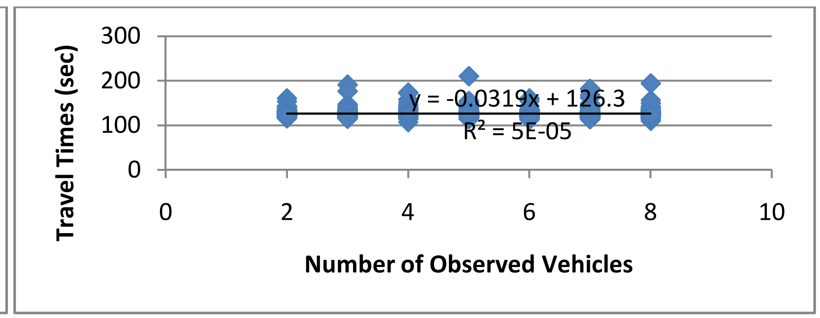
(a) Travel Time Segment #1



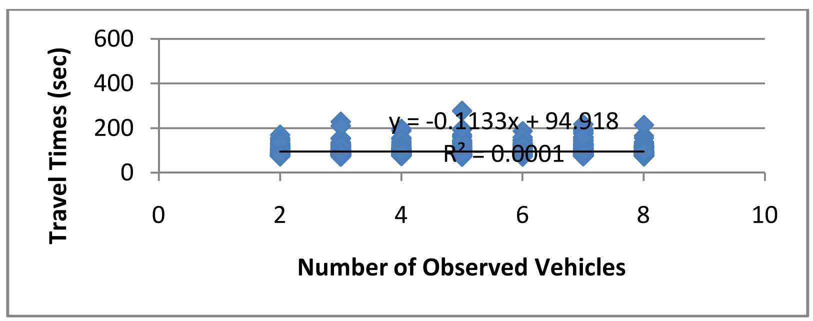
(b) Travel Time Segment #2



(c) Travel Time Segment #3

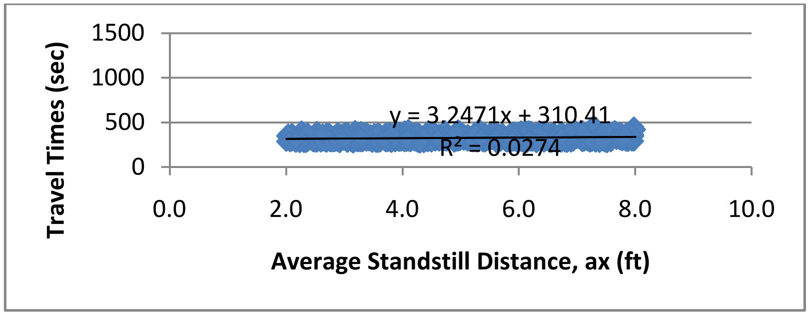


(d) Travel Time Segment #4

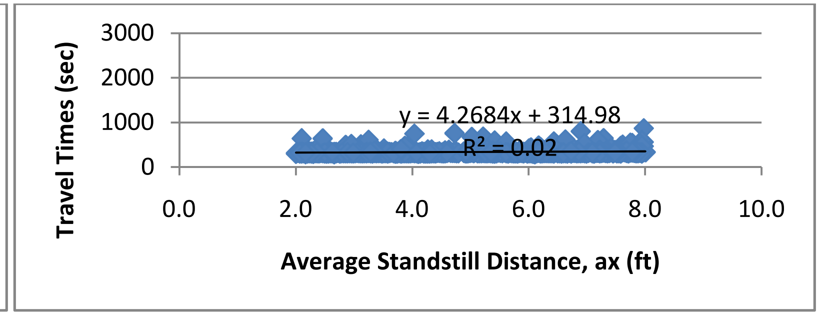


(e) Travel Time Segment #5

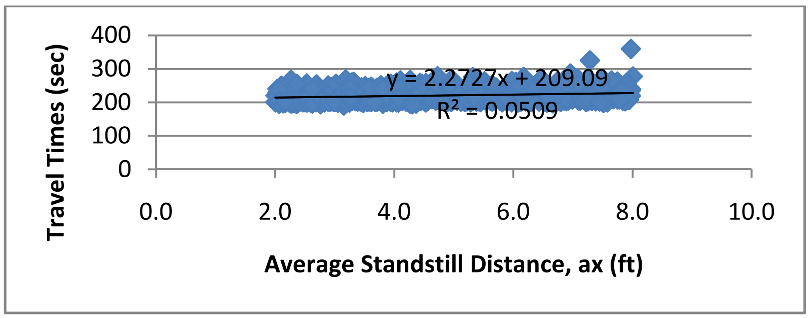
Figure 29(a-e): 100% Volume Scenario, Iteration #1, Parameter #4 Scatter Plots



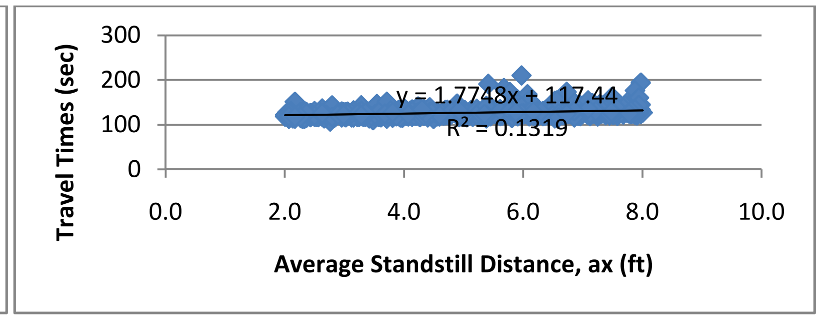
(a) Travel Time Segment #1



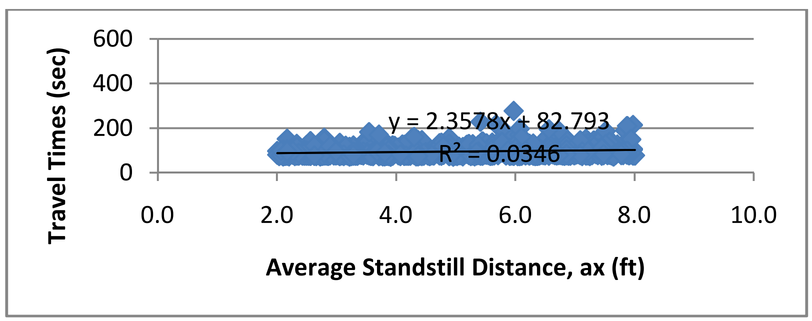
(b) Travel Time Segment #2



(c) Travel Time Segment #3

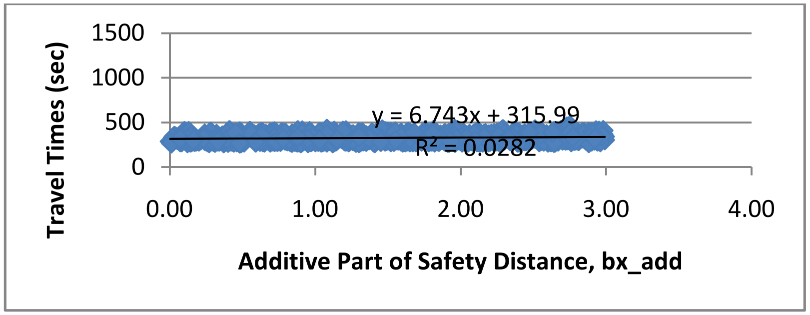


(d) Travel Time Segment #4

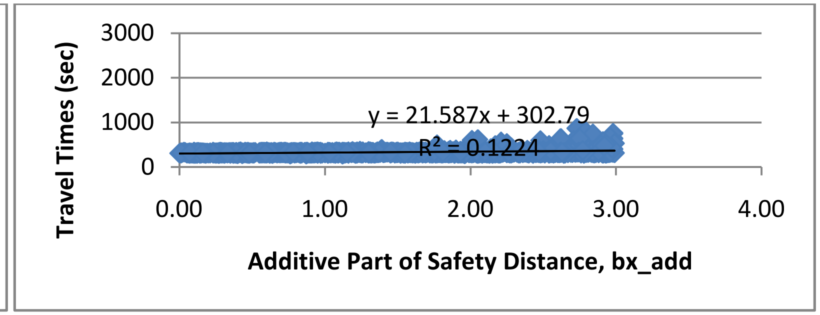


(e) Travel Time Segment #5

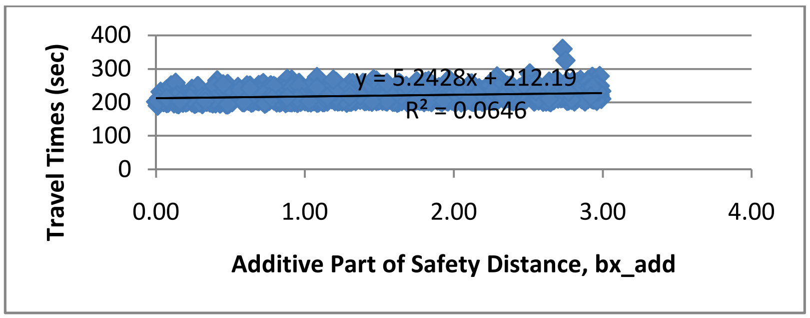
Figure 30(a-e): 100% Volume Scenario, Iteration #1, Parameter #5 Scatter Plots



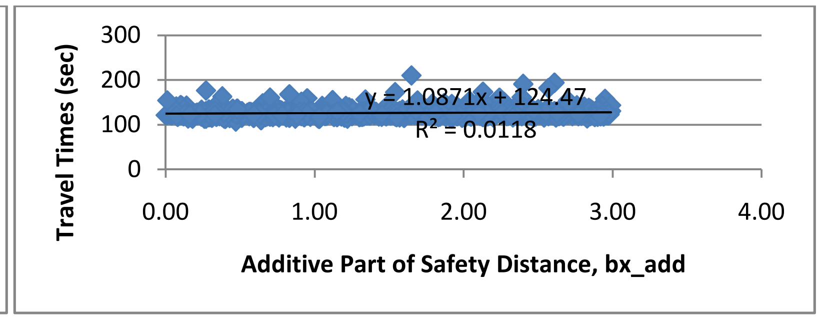
(a) Travel Time Segment #1



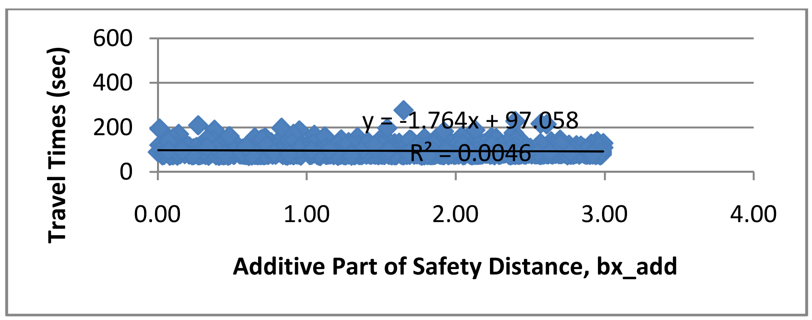
(b) Travel Time Segment #2



(c) Travel Time Segment #3

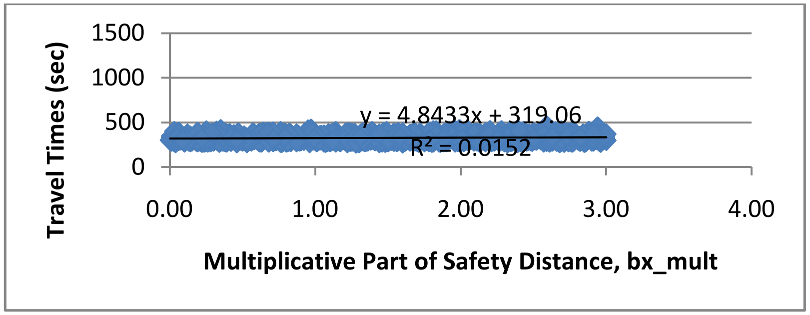


(d) Travel Time Segment #4

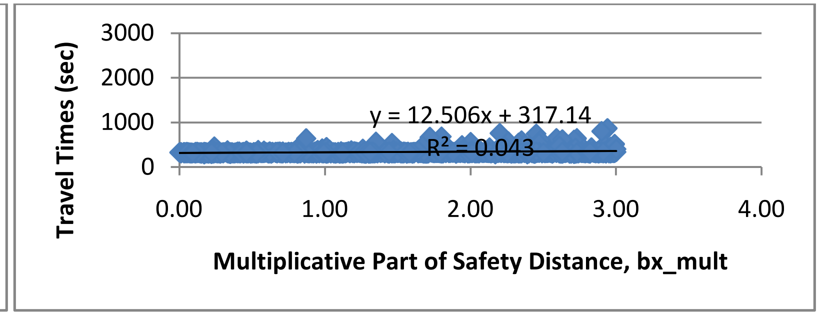


(e) Travel Time Segment #5

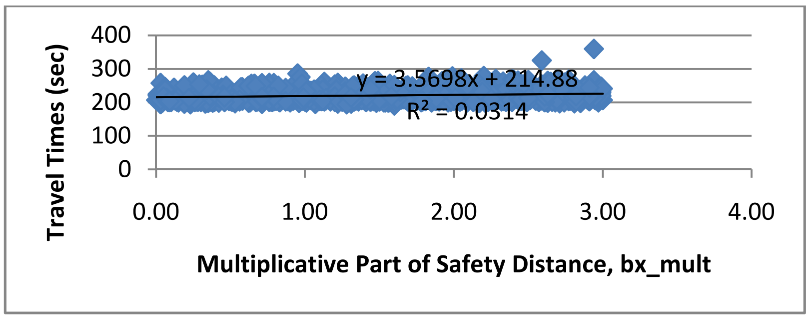
Figure 31(a-e): 100% Volume Scenario, Iteration #1, Parameter #6 Scatter Plots



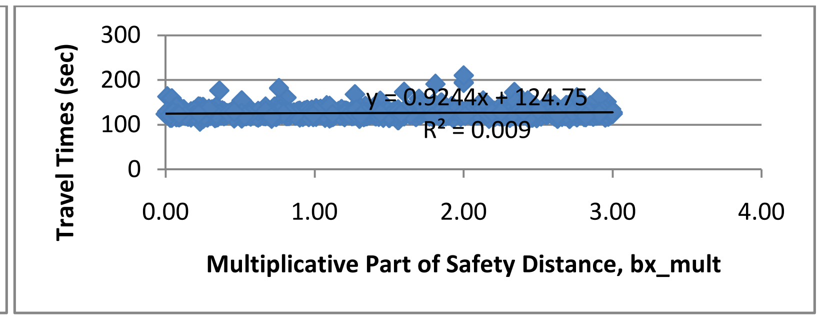
(a) Travel Time Segment #1



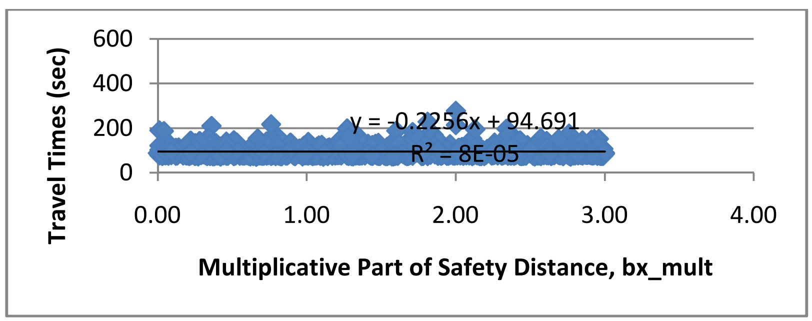
(b) Travel Time Segment #2



(c) Travel Time Segment #3

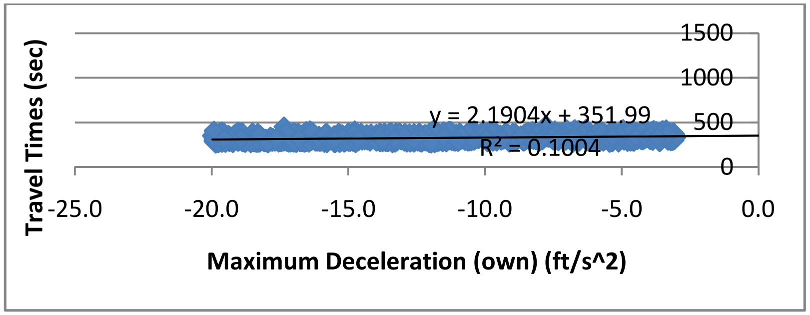


(d) Travel Time Segment #4

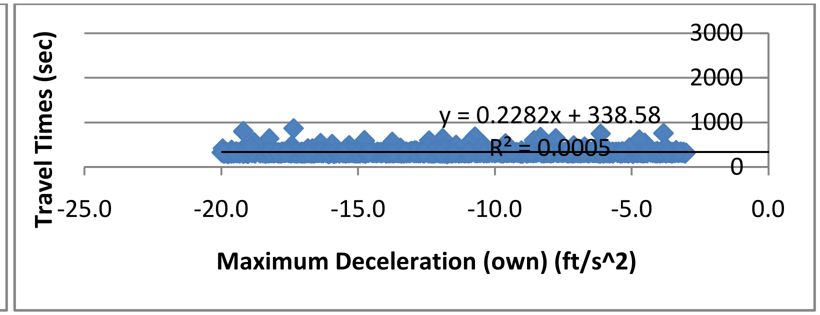


(e) Travel Time Segment #5

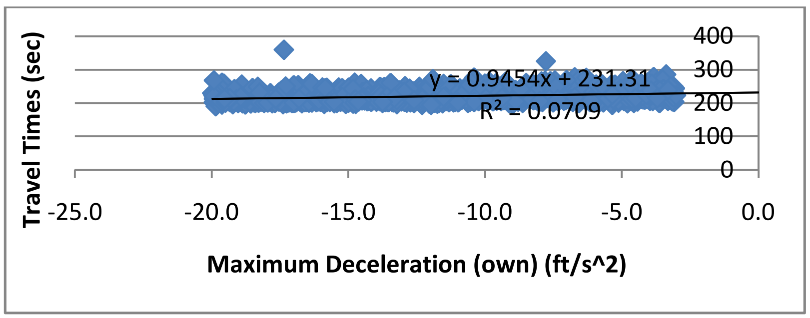
Figure 32(a-e): 100% Volume Scenario, Iteration #1, Parameter #7 Scatter Plots



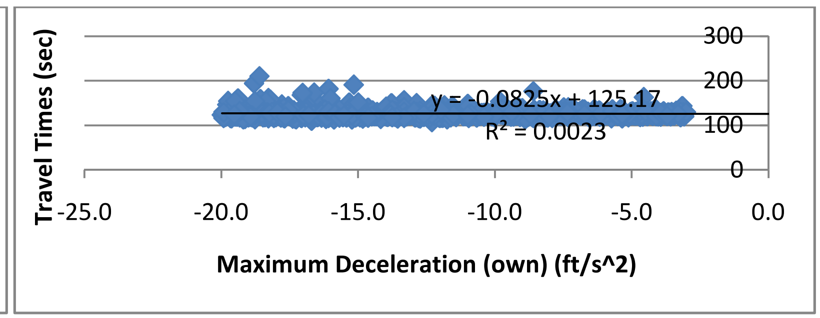
(a) Travel Time Segment #1



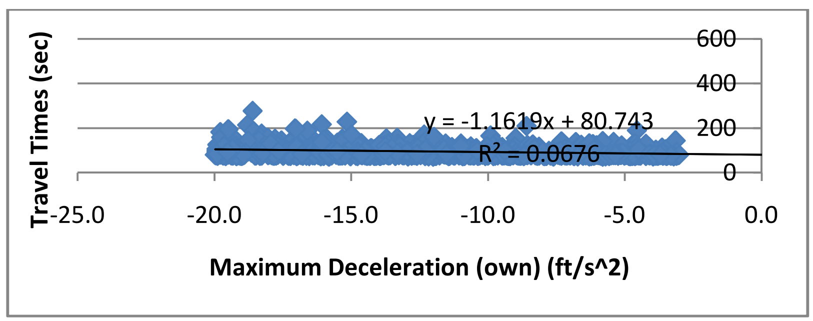
(b) Travel Time Segment #2



(c) Travel Time Segment #3

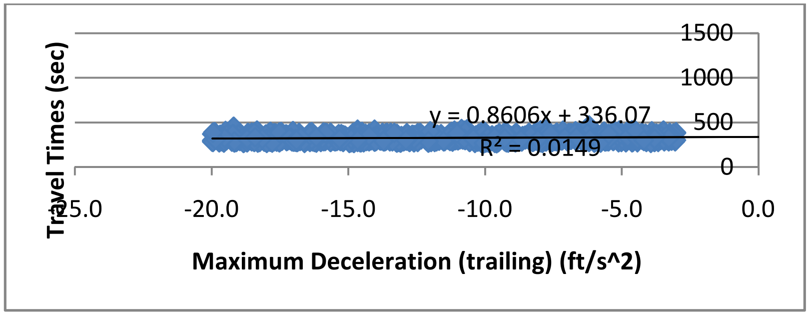


(d) Travel Time Segment #4

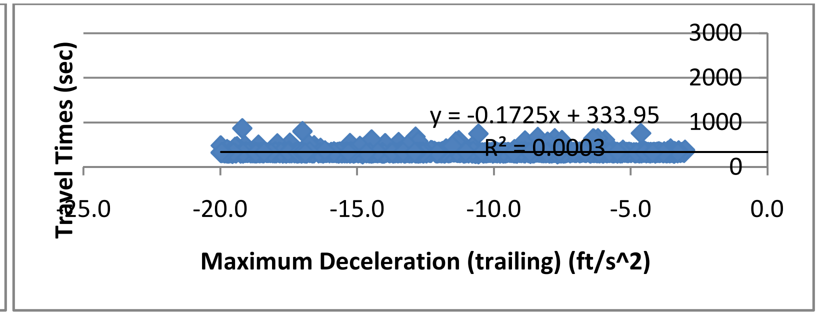


(e) Travel Time Segment #5

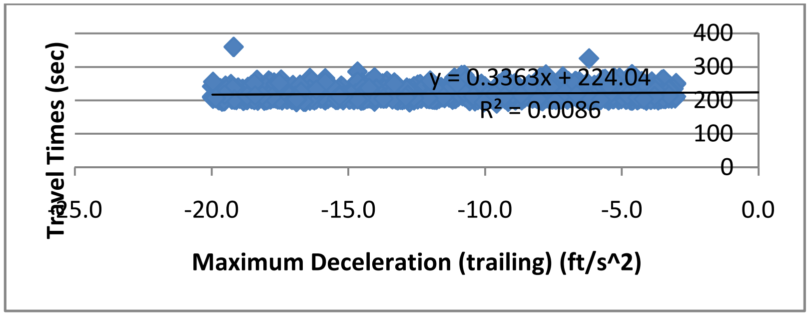
Figure 33(a-e): 100% Volume Scenario, Iteration #1, Parameter #8 Scatter Plots



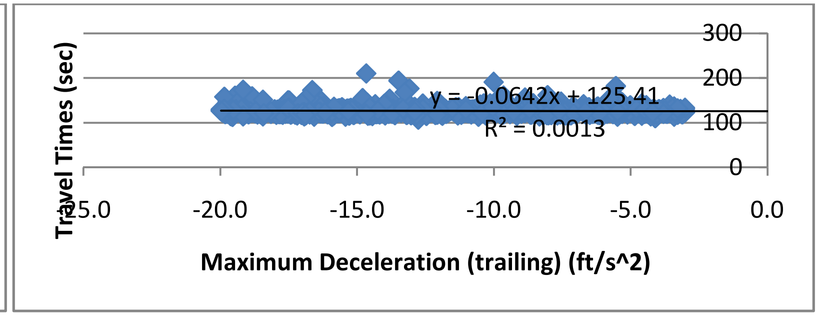
(a) Travel Time Segment #1



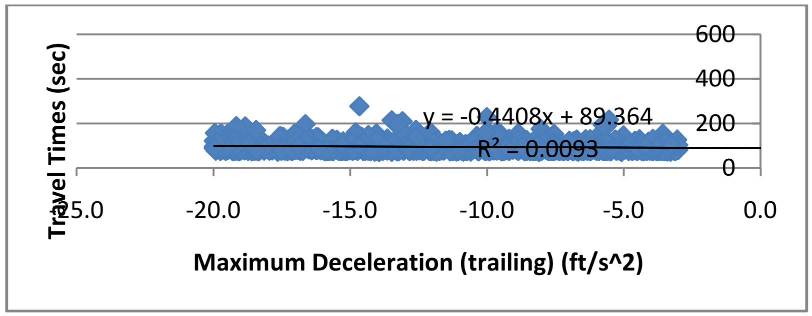
(b) Travel Time Segment #2



(c) Travel Time Segment #3

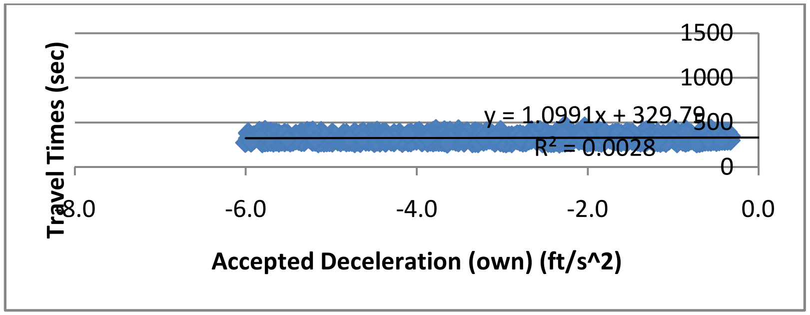


(d) Travel Time Segment #4

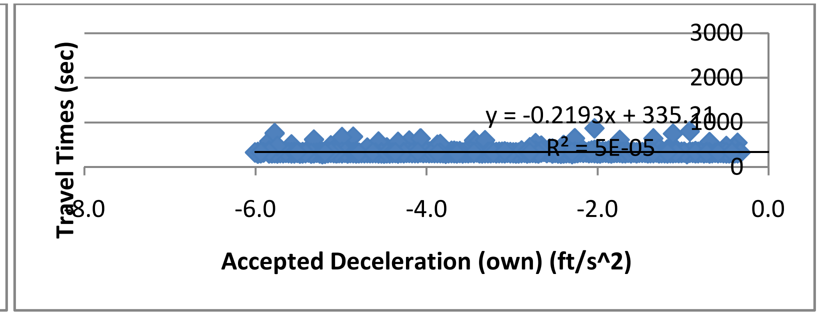


(e) Travel Time Segment #5

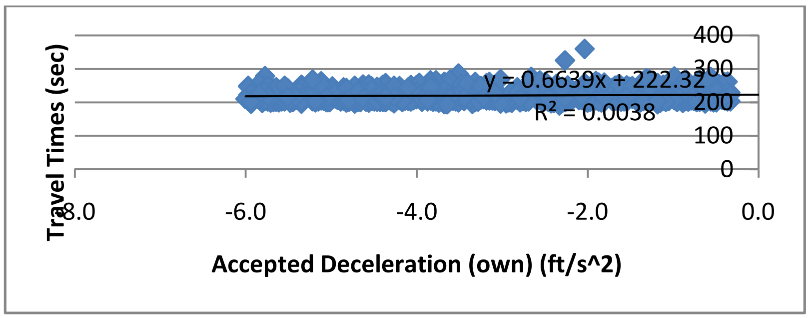
Figure 34(a-e): 100% Volume Scenario, Iteration #1, Parameter #9 Scatter Plots



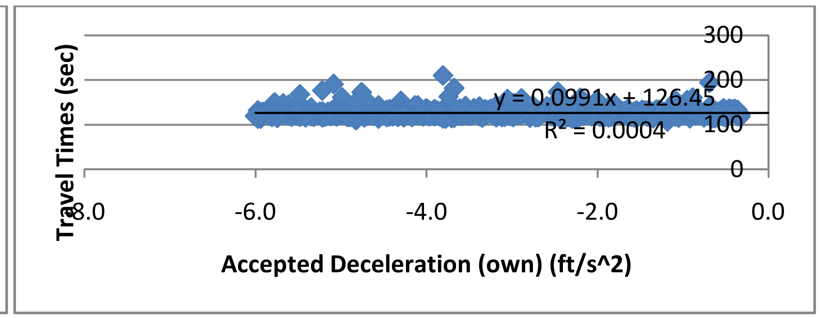
(a) Travel Time Segment #1



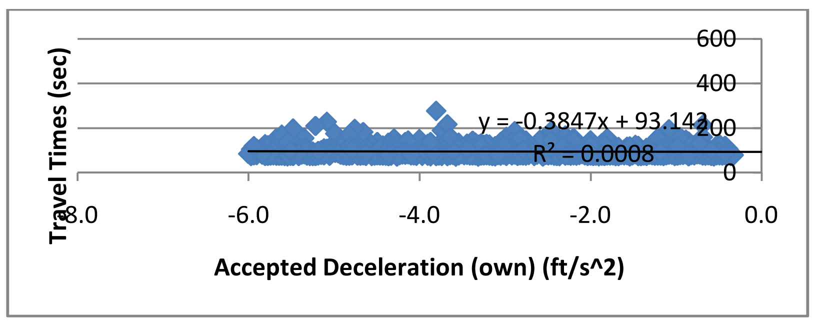
(b) Travel Time Segment #2



(c) Travel Time Segment #3

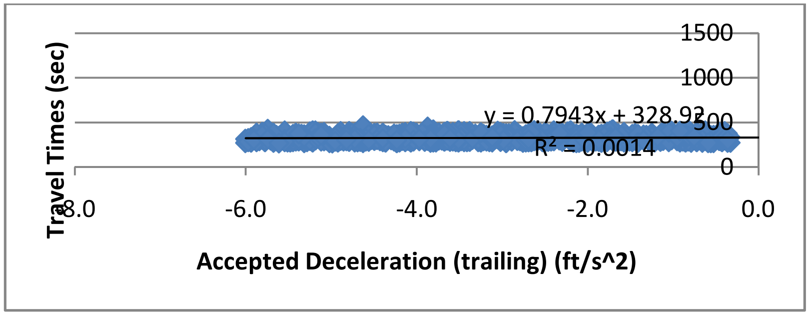


(d) Travel Time Segment #4

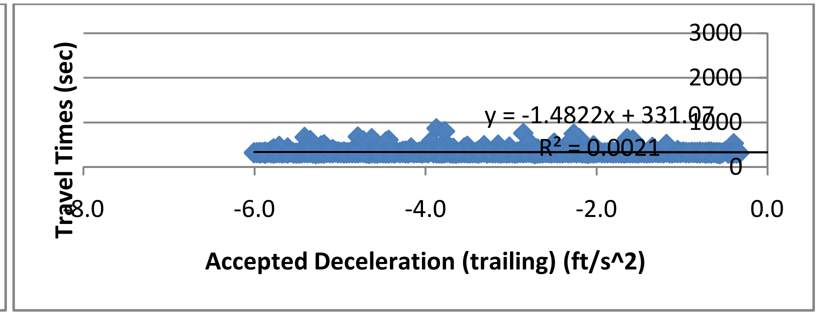


(e) Travel Time Segment #5

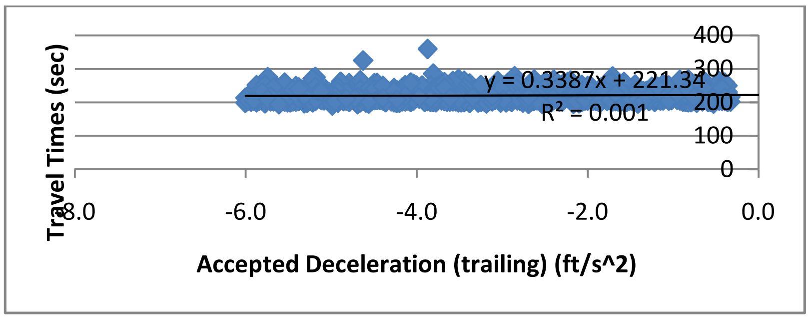
Figure 35(a-e): 100% Volume Scenario, Iteration #1, Parameter #10 Scatter Plots



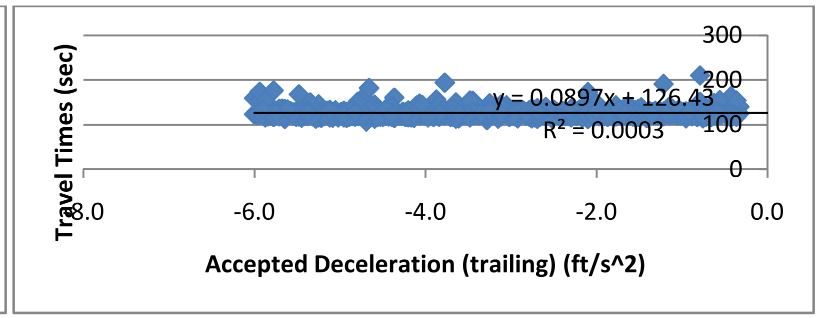
(a) Travel Time Segment #1



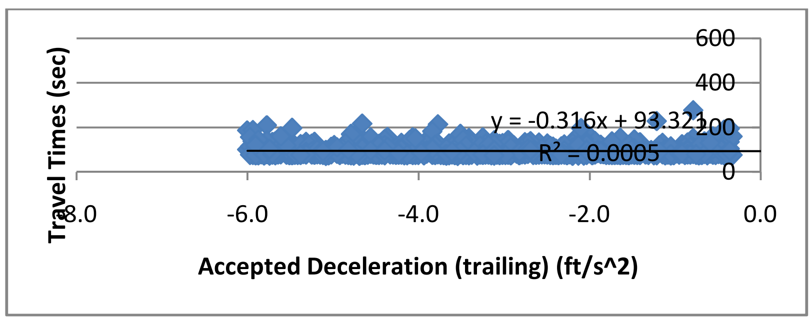
(b) Travel Time Segment #2



(c) Travel Time Segment #3

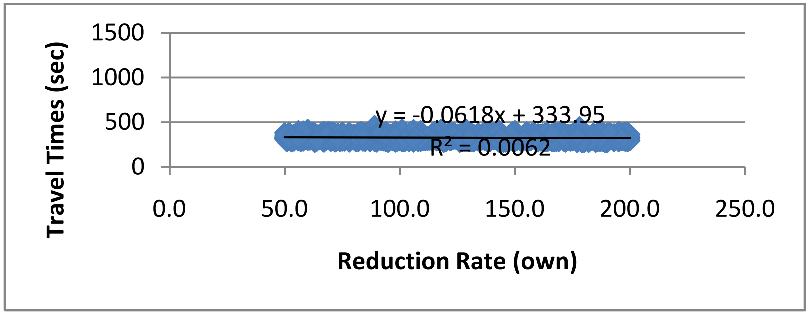


(d) Travel Time Segment #4

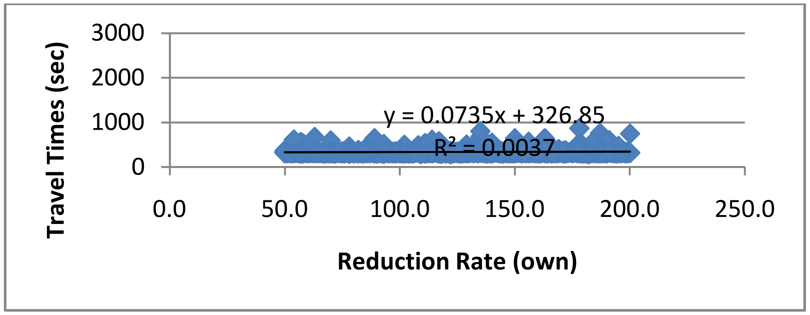


(e) Travel Time Segment #5

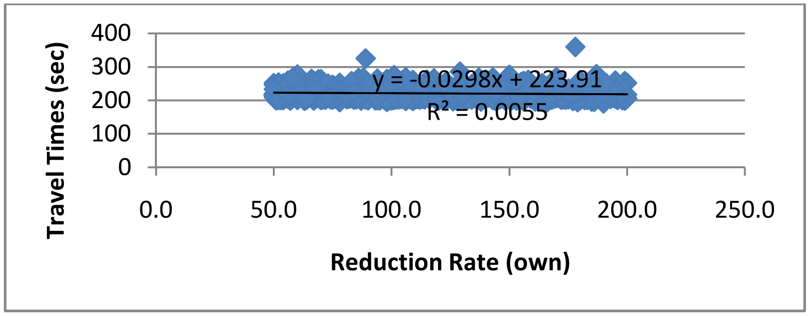
Figure 36(a-e): 100% Volume Scenario, Iteration #1, Parameter #11 Scatter Plots



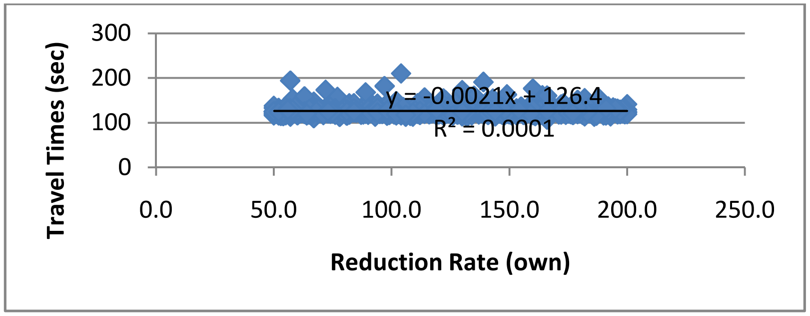
(a) Travel Time Segment #1



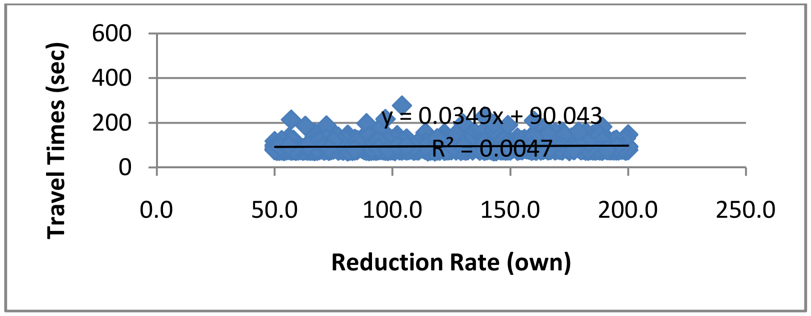
(b) Travel Time Segment #2



(c) Travel Time Segment #3

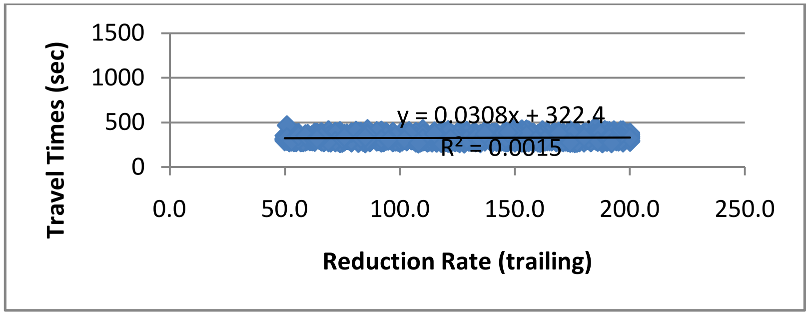


(d) Travel Time Segment #4

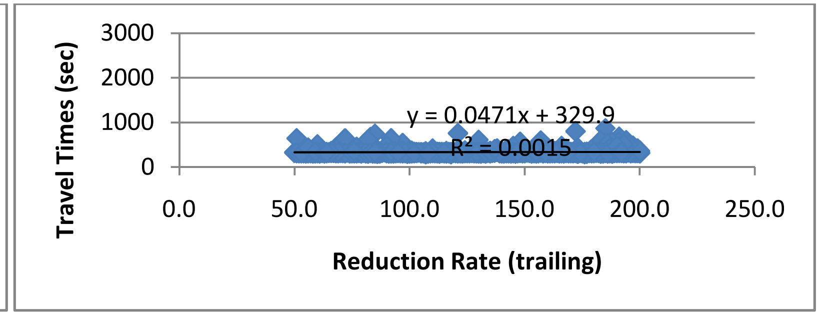


(e) Travel Time Segment #5

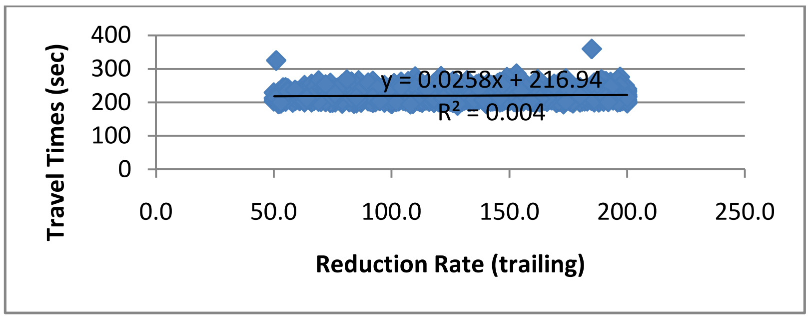
Figure 37(a-e): 100% Volume Scenario, Iteration #1, Parameter #12 Scatter Plots



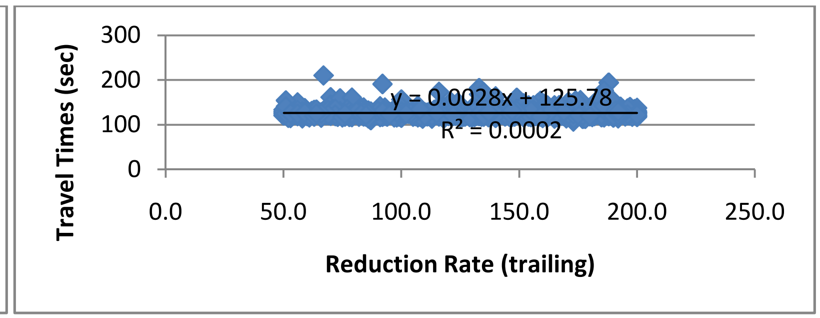
(a) Travel Time Segment #1



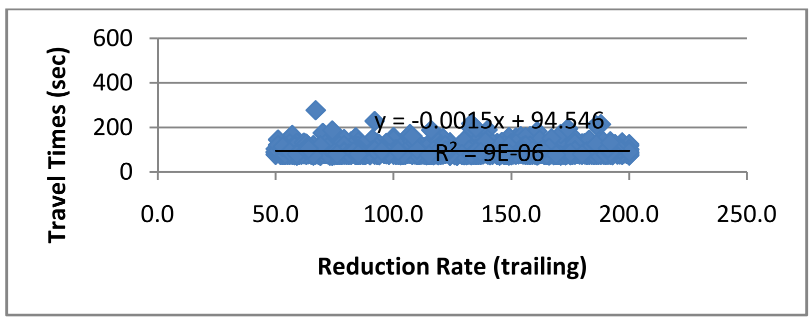
(b) Travel Time Segment #2



(c) Travel Time Segment #3

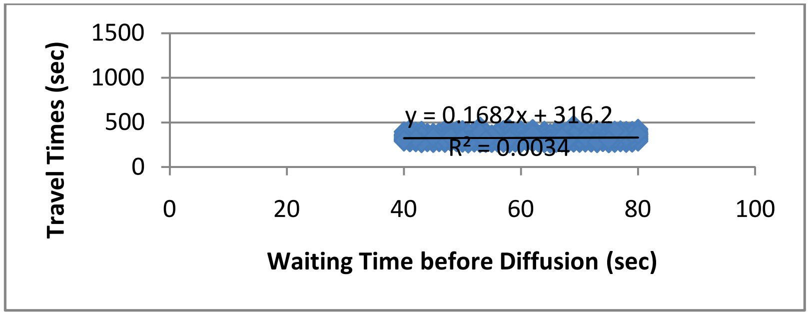


(d) Travel Time Segment #4

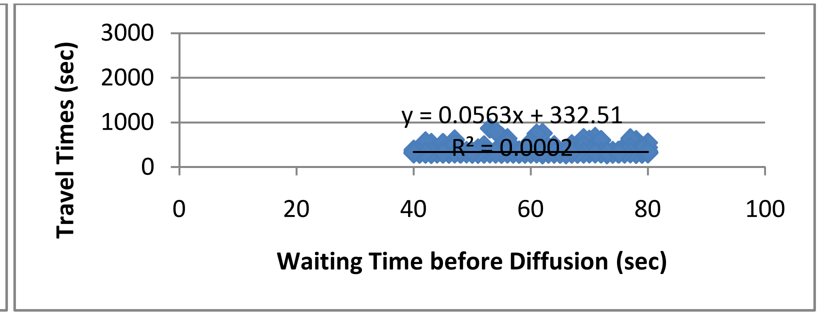


(e) Travel Time Segment #5

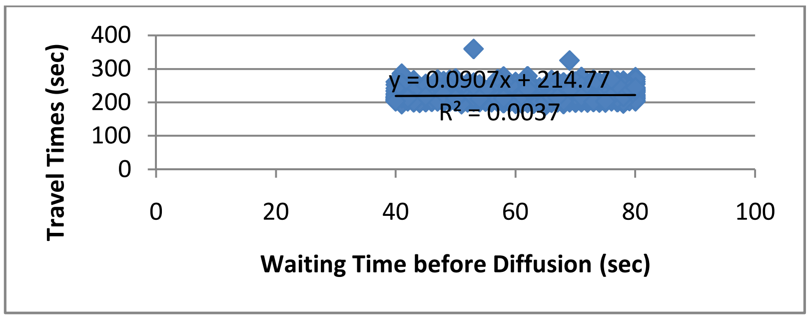
Figure 38(a-e): 100% Volume Scenario, Iteration #1, Parameter #13 Scatter Plots



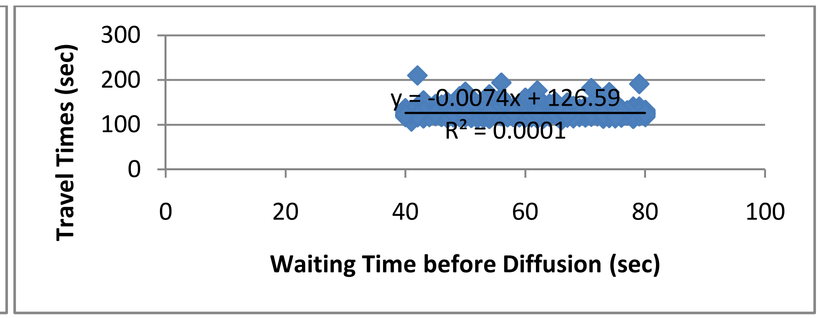
(a) Travel Time Segment #1



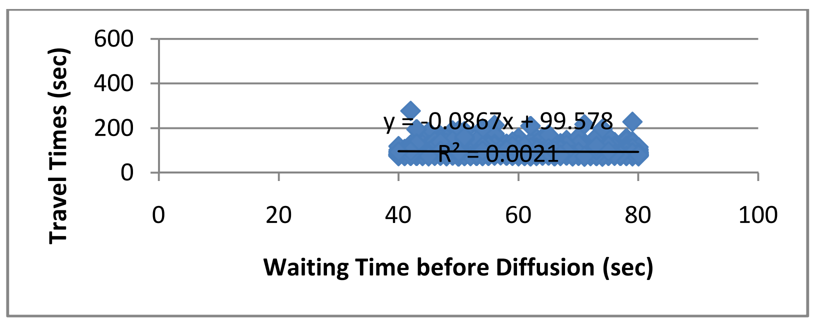
(b) Travel Time Segment #2



(c) Travel Time Segment #3

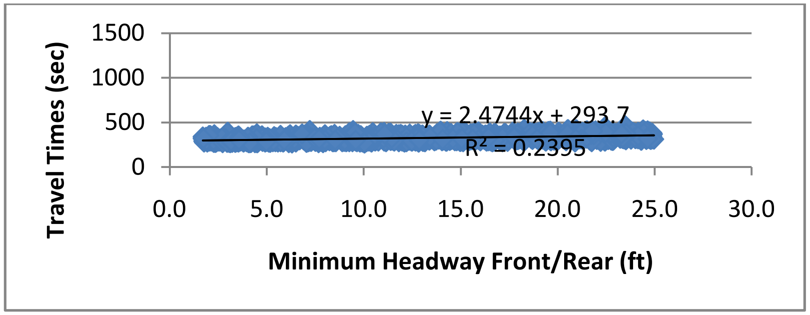


(d) Travel Time Segment #4

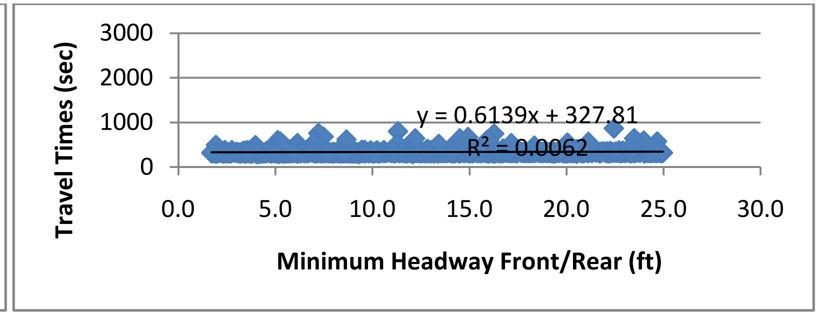


(e) Travel Time Segment #5

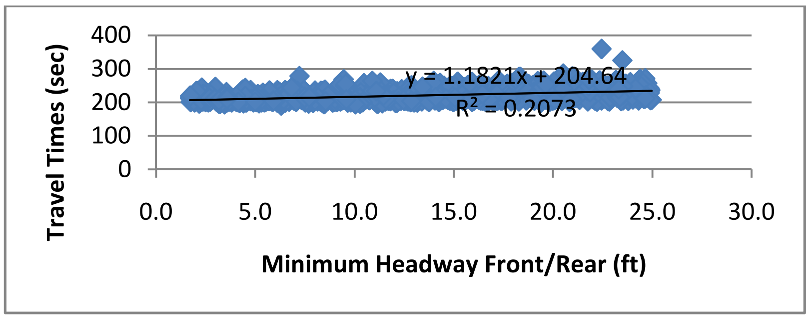
Figure 39(a-e): 100% Volume Scenario, Iteration #1, Parameter #14 Scatter Plots



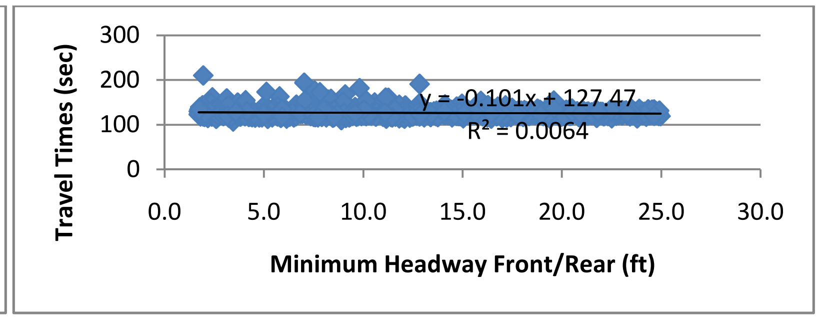
(a) Travel Time Segment #1



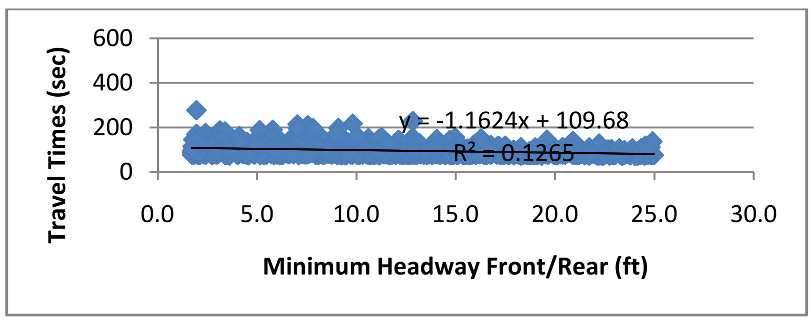
(b) Travel Time Segment #2



(c) Travel Time Segment #3

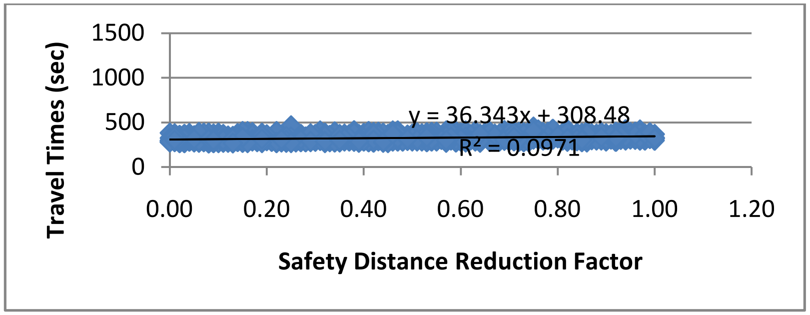


(d) Travel Time Segment #4

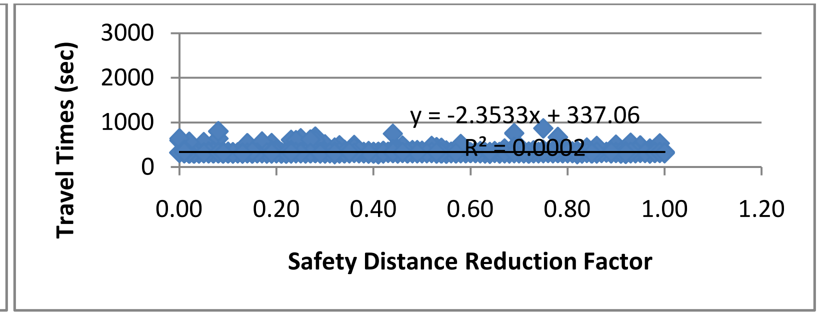


(e) Travel Time Segment #5

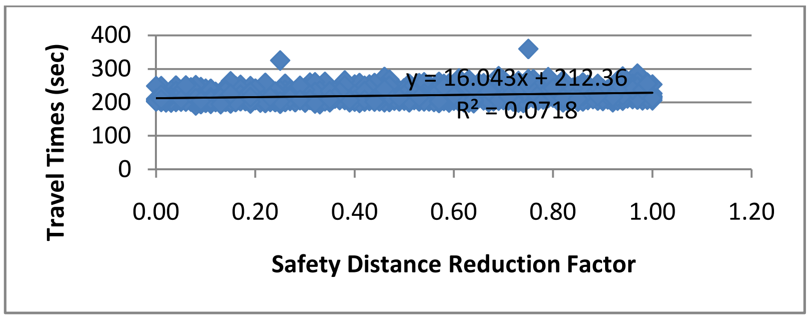
Figure 40(a-e): 100% Volume Scenario, Iteration #1, Parameter #15 Scatter Plots



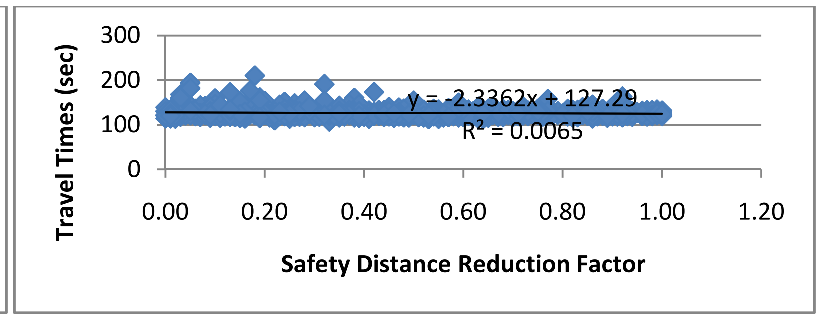
(a) Travel Time Segment #1



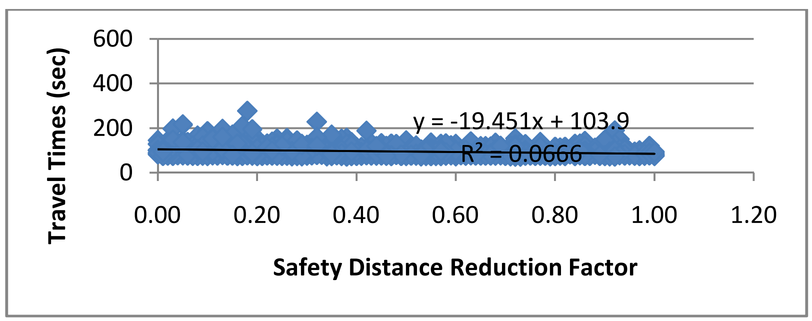
(b) Travel Time Segment #2



(c) Travel Time Segment #3

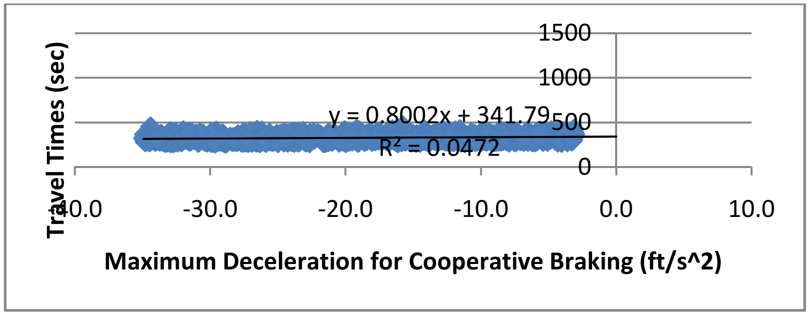


(d) Travel Time Segment #4

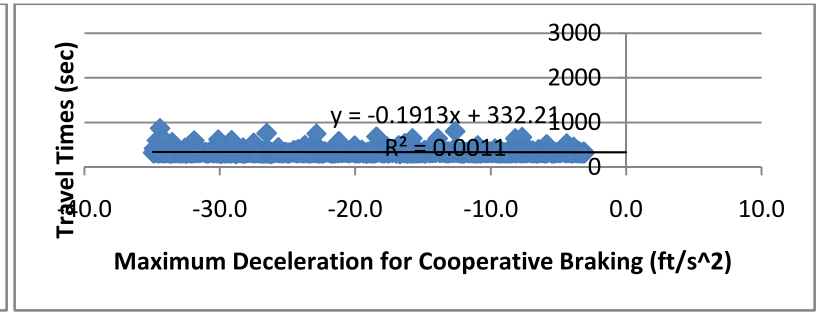


(e) Travel Time Segment #5

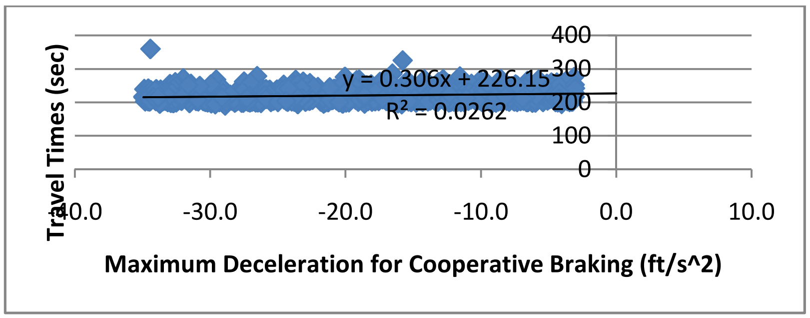
Figure 41(a-e): 100% Volume Scenario, Iteration #1, Parameter #16 Scatter Plots



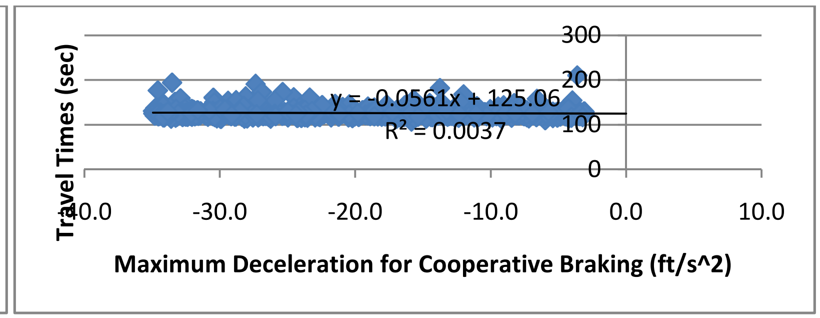
(a) Travel Time Segment #1



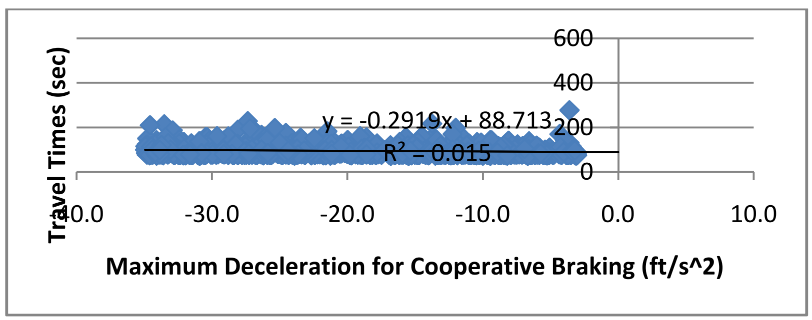
(b) Travel Time Segment #2



(c) Travel Time Segment #3

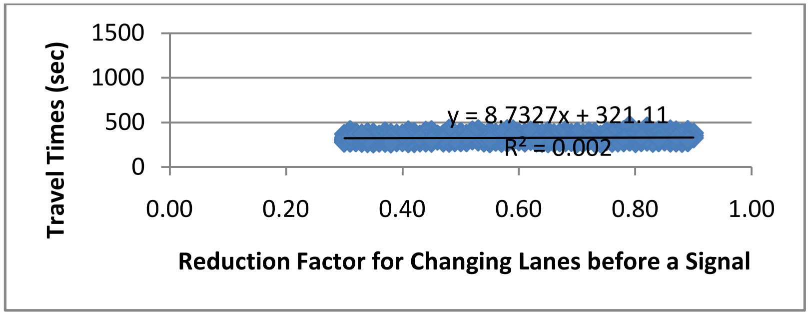


(d) Travel Time Segment #4

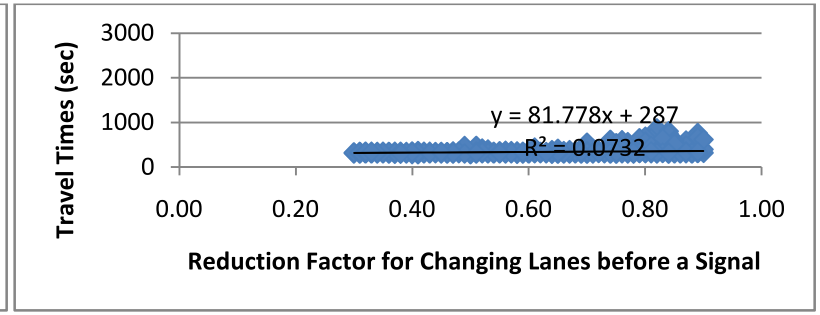


(e) Travel Time Segment #5

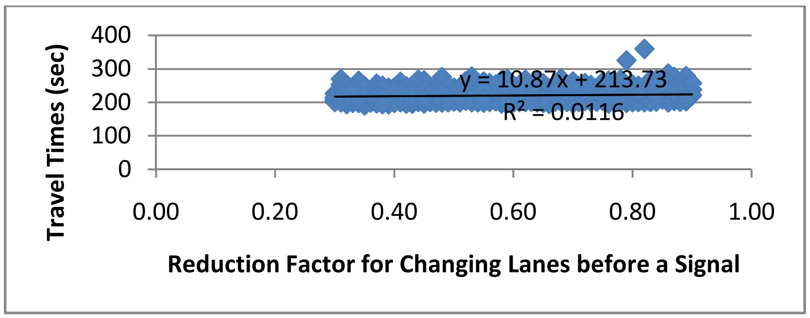
Figure 42(a-e): 100% Volume Scenario, Iteration #1, Parameter #17 Scatter Plots



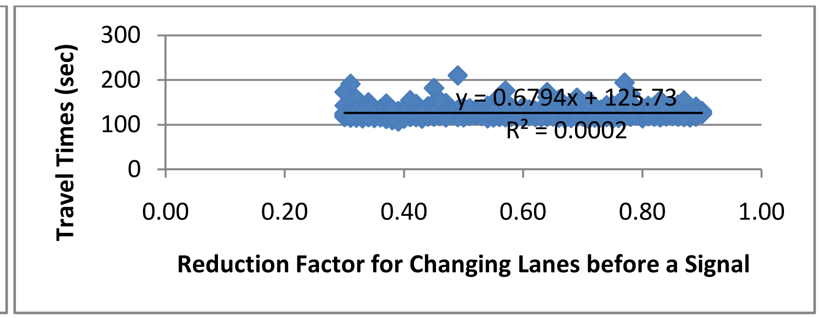
(a) Travel Time Segment #1



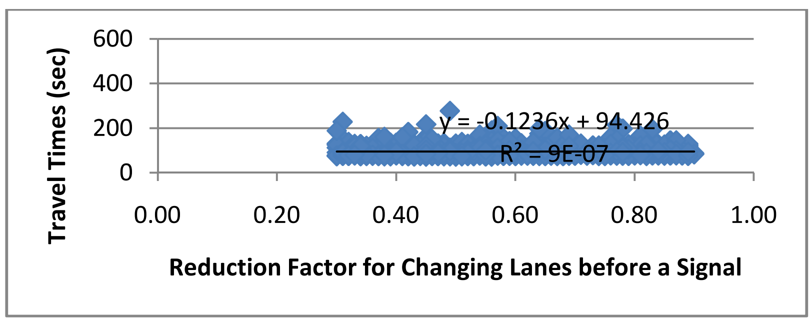
(b) Travel Time Segment #2



(c) Travel Time Segment #3

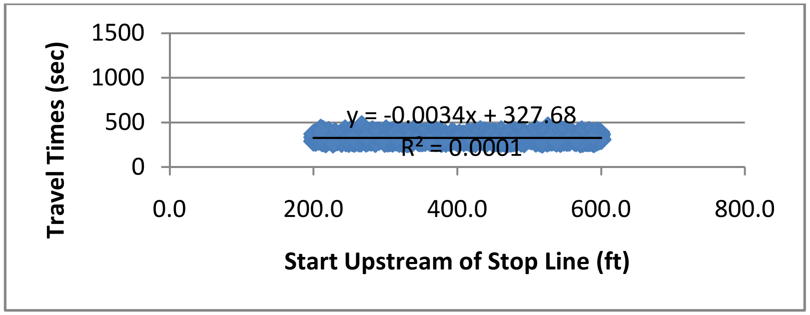


(d) Travel Time Segment #4

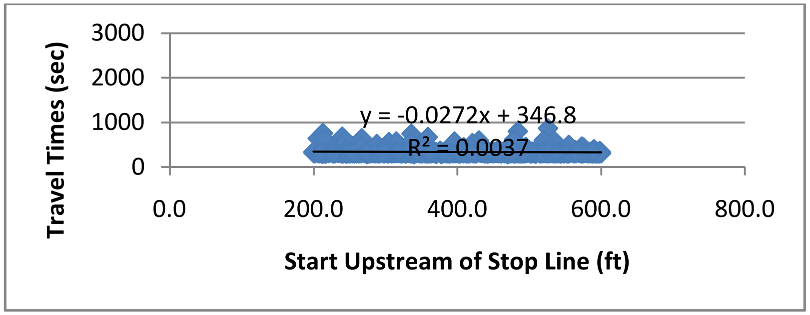


(e) Travel Time Segment #5

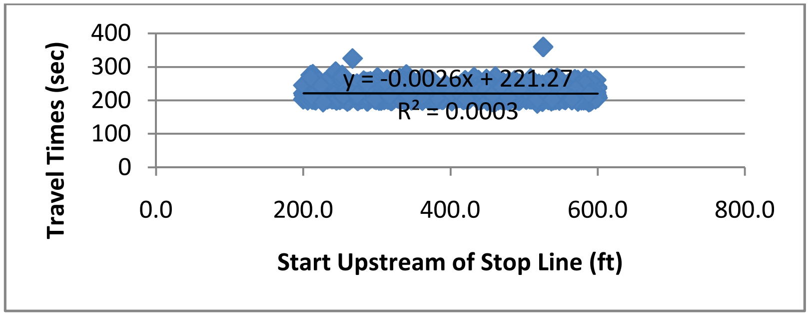
Figure 43(a-e): 100% Volume Scenario, Iteration #1, Parameter #18 Scatter Plots



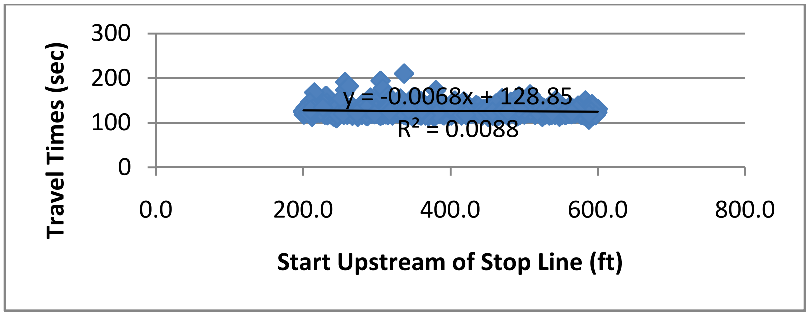
(a) Travel Time Segment #1



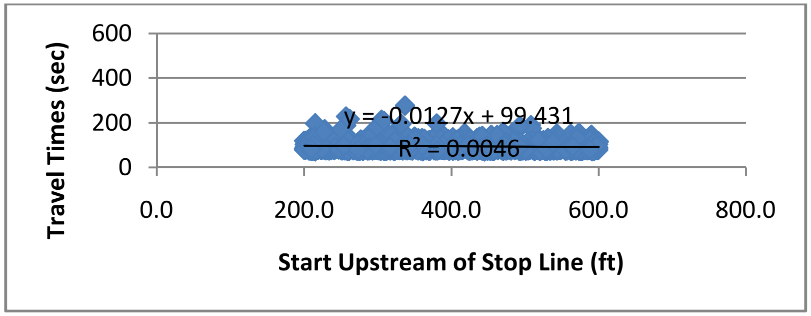
(b) Travel Time Segment #2



(c) Travel Time Segment #3

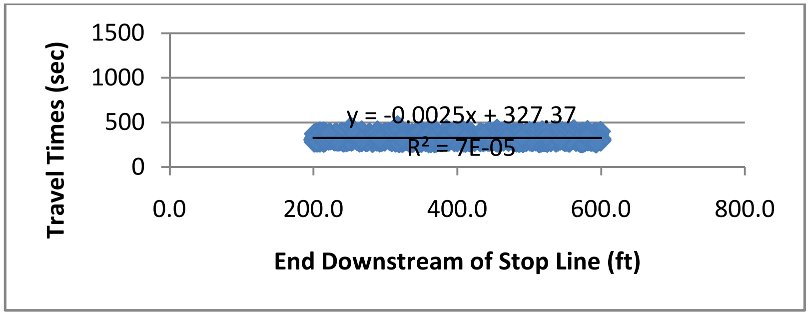


(d) Travel Time Segment #4

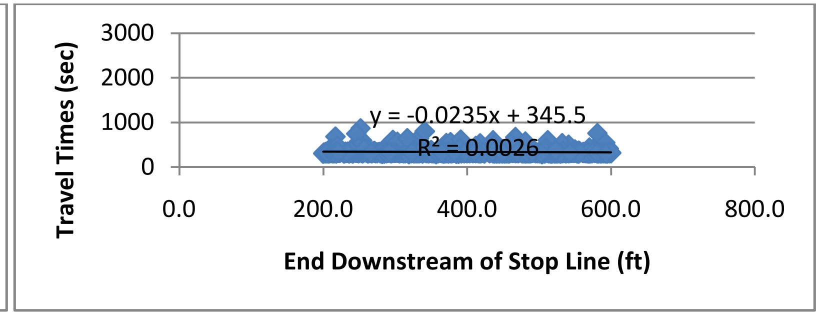


(e) Travel Time Segment #5

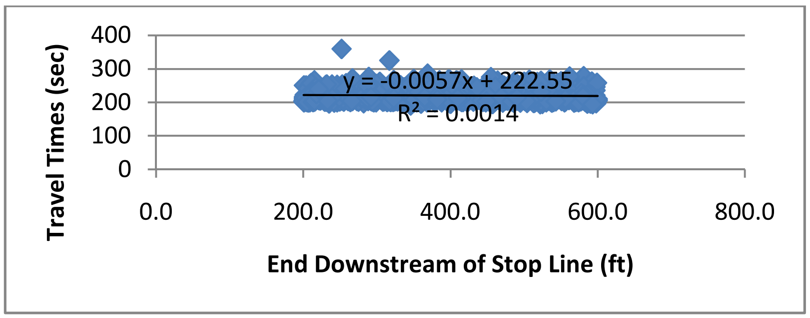
Figure 44(a-e): 100% Volume Scenario, Iteration #1, Parameter #19 Scatter Plots



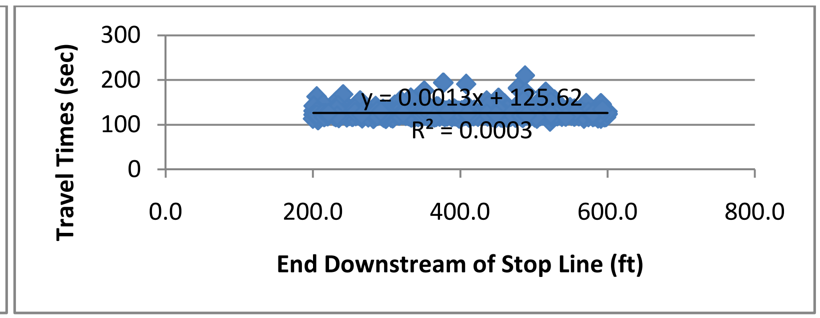
(a) Travel Time Segment #1



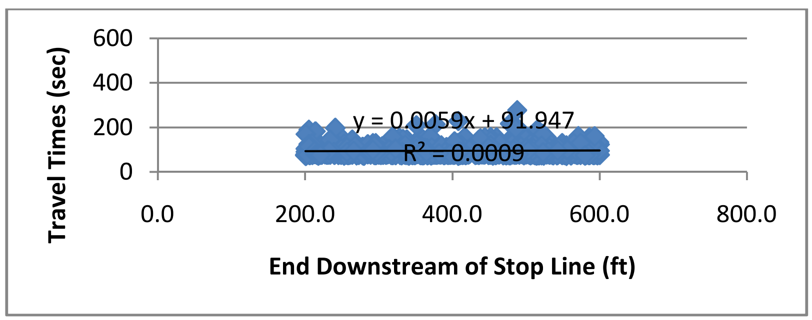
(b) Travel Time Segment #2



(c) Travel Time Segment #3

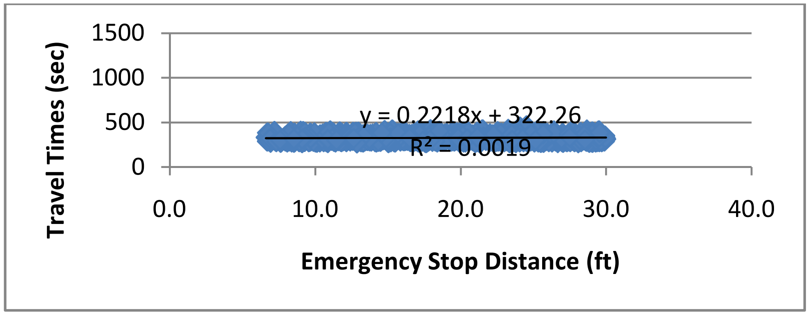


(d) Travel Time Segment #4

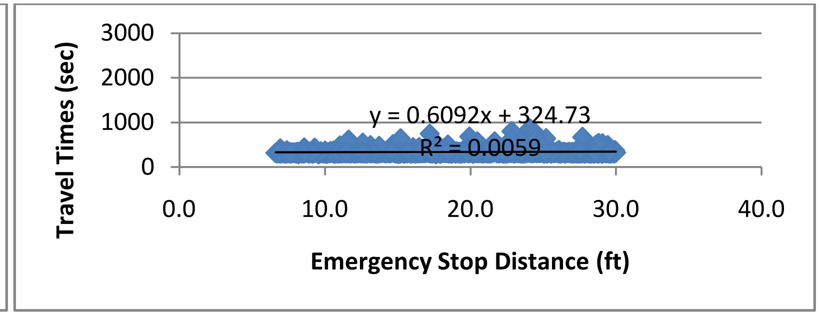


(e) Travel Time Segment #5

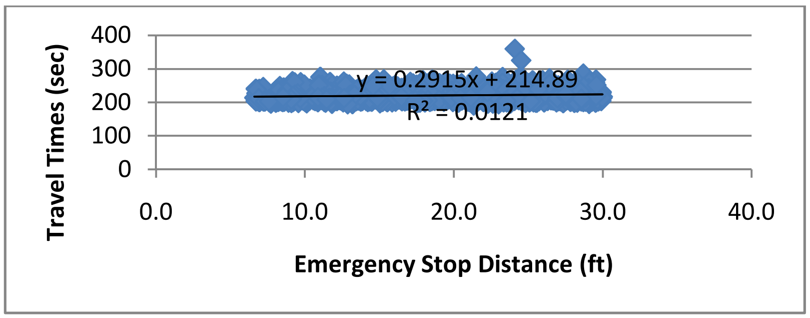
Figure 45(a-e): 100% Volume Scenario, Iteration #1, Parameter #20 Scatter Plots



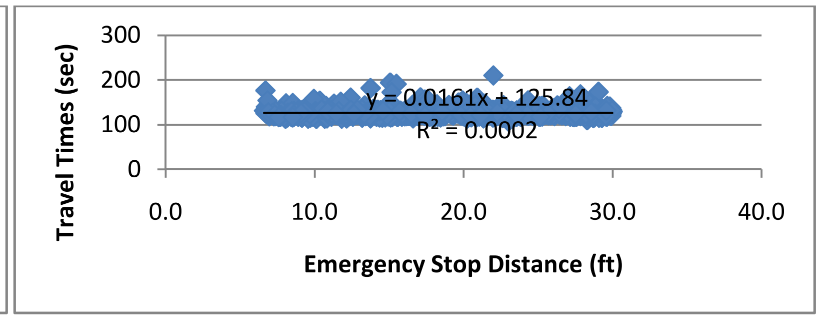
(a) Travel Time Segment #1



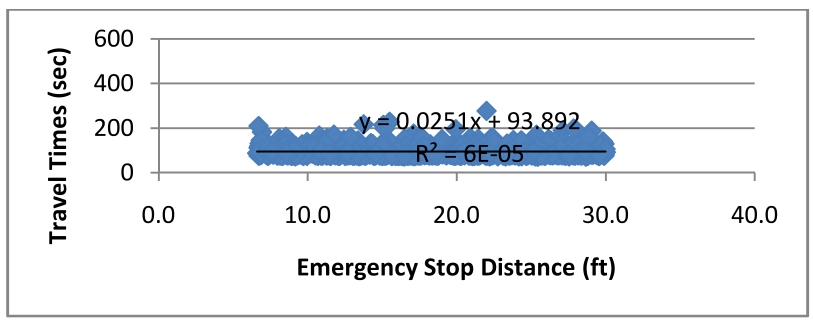
(b) Travel Time Segment #2



(c) Travel Time Segment #3

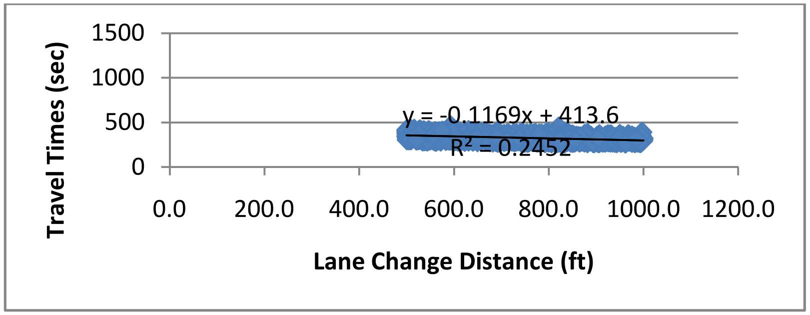


(d) Travel Time Segment #4

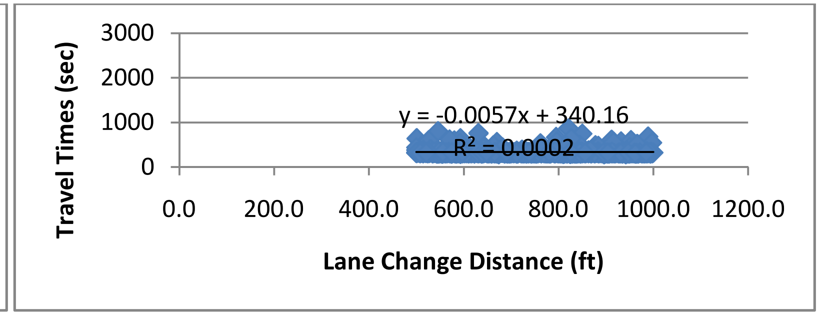


(e) Travel Time Segment #5

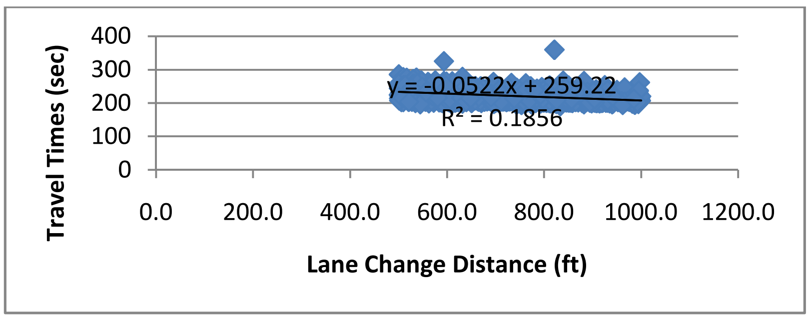
Figure 46(a-e): 100% Volume Scenario, Iteration #1, Parameter #21 Scatter Plots



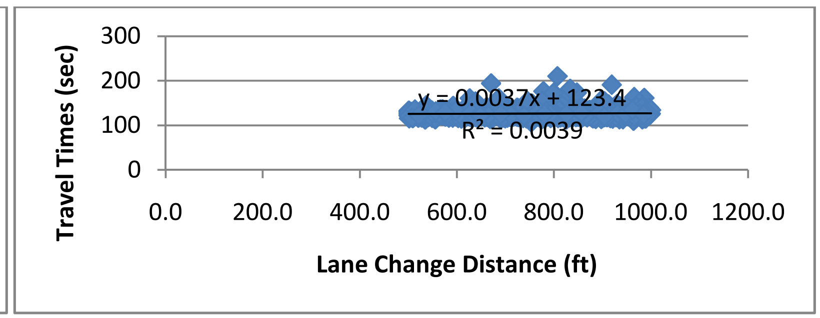
(a) Travel Time Segment #1



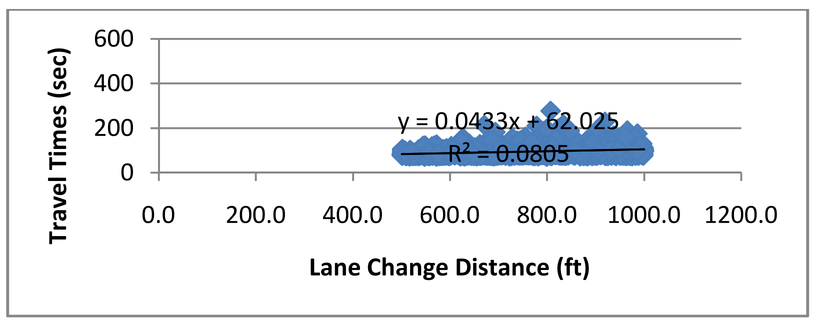
(b) Travel Time Segment #2



(c) Travel Time Segment #3

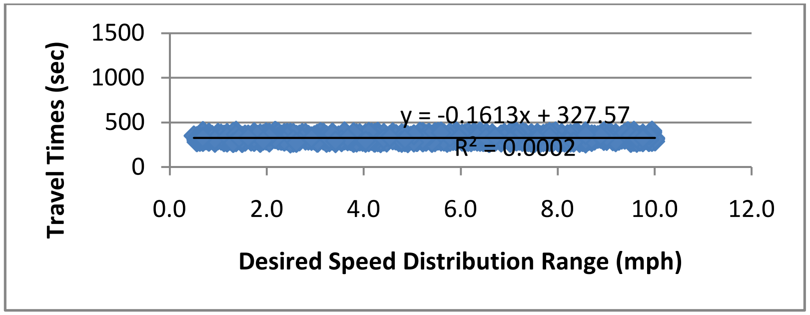


(d) Travel Time Segment #4

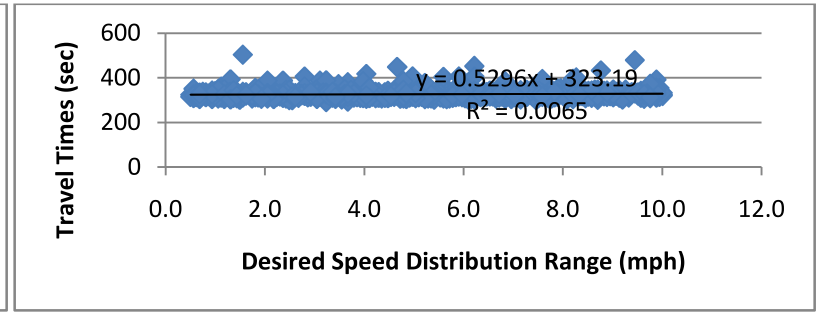


(e) Travel Time Segment #5

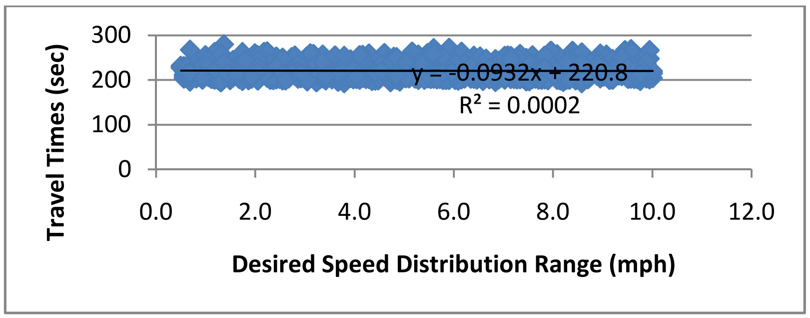
Figure 47(a-e): 100% Volume Scenario, Iteration #1, Parameter #22 Scatter Plots



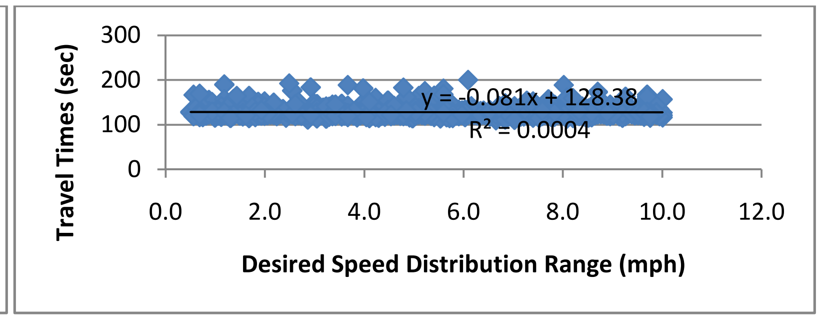
(a) Travel Time Segment #1



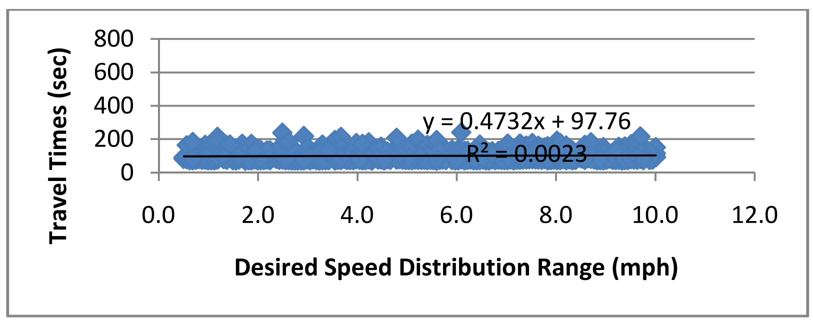
(b) Travel Time Segment #2



(c) Travel Time Segment #3

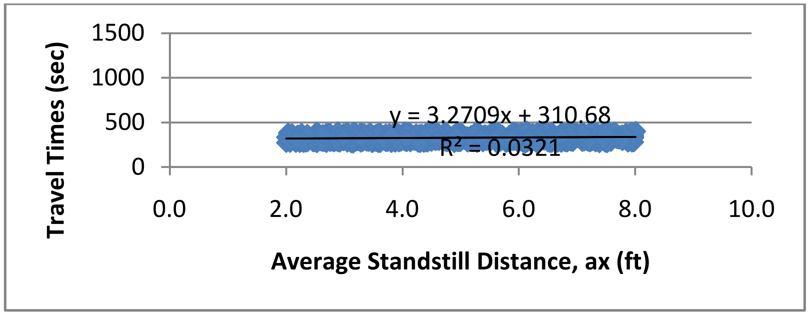


(d) Travel Time Segment #4

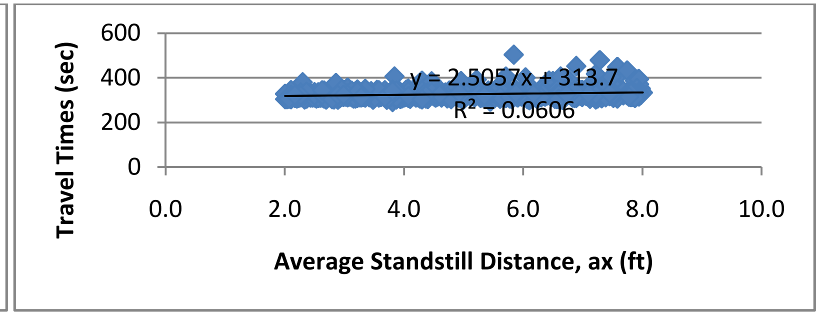


(e) Travel Time Segment #5

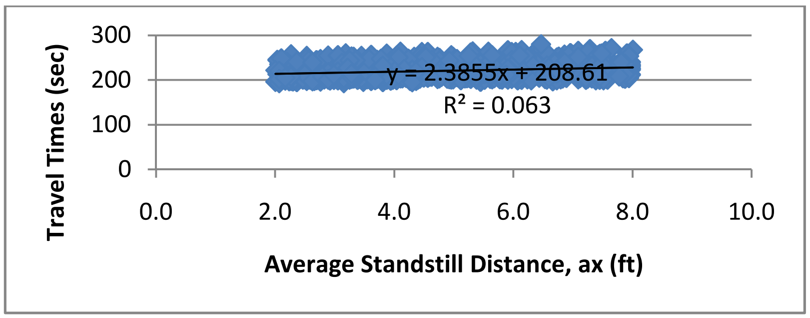
Figure 48(a-e): 100% Volume Scenario, Iteration #2, Parameter #1 Scatter Plots



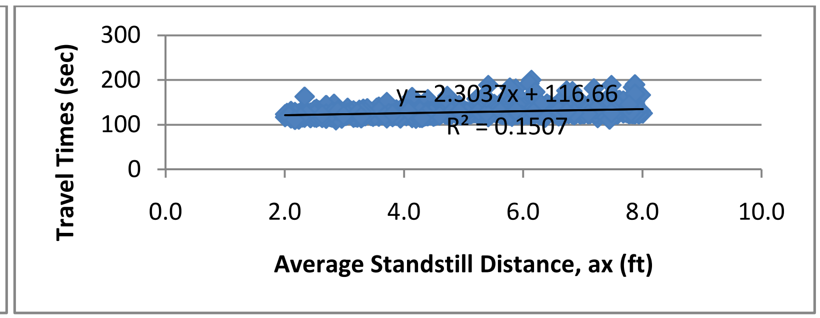
(a) Travel Time Segment #1



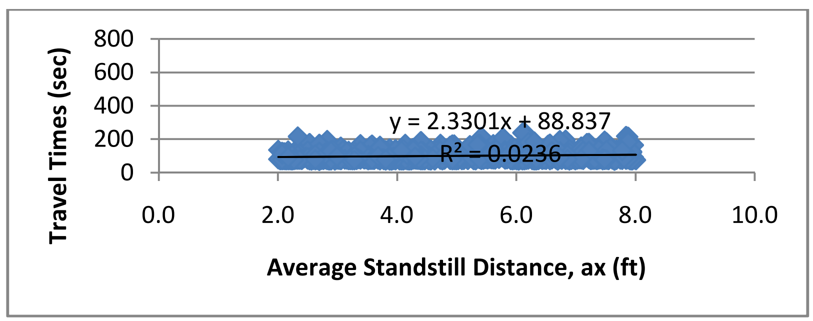
(b) Travel Time Segment #2



(c) Travel Time Segment #3

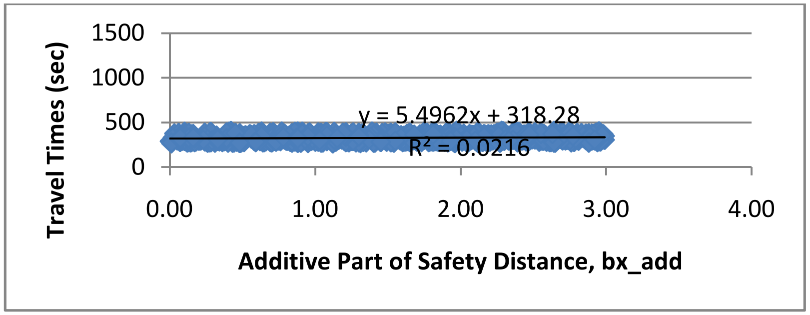


(d) Travel Time Segment #4

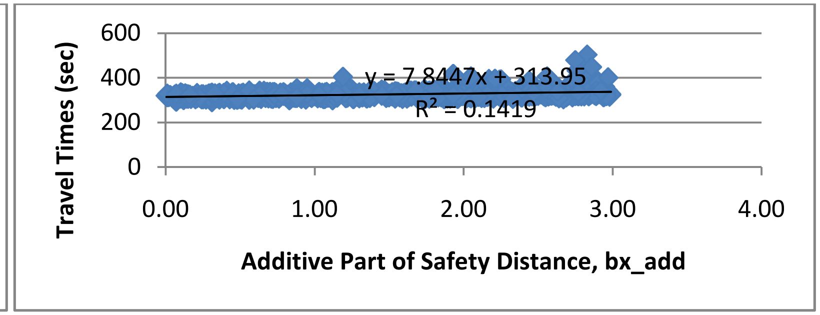


(e) Travel Time Segment #5

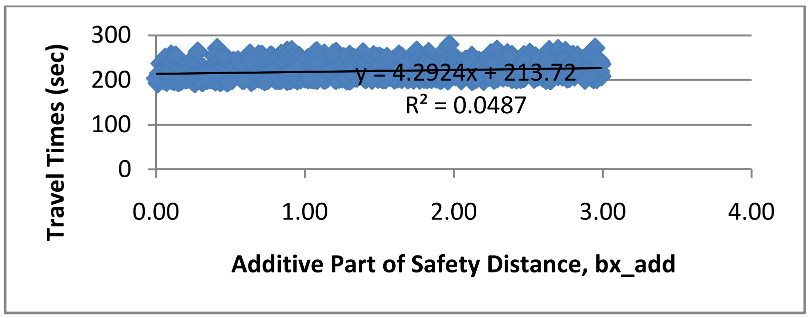
Figure 49(a-e): 100% Volume Scenario, Iteration #2, Parameter #5 Scatter Plots



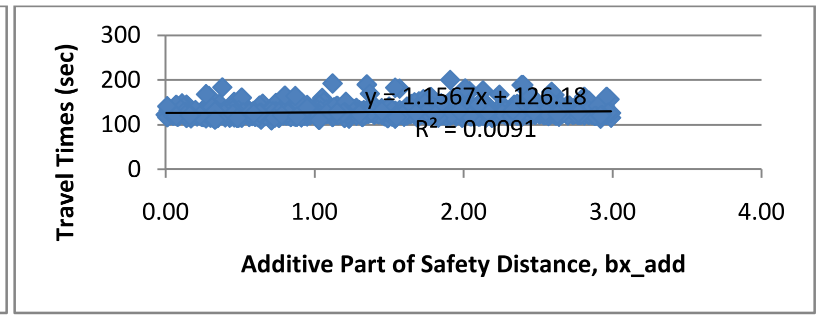
(a) Travel Time Segment #1



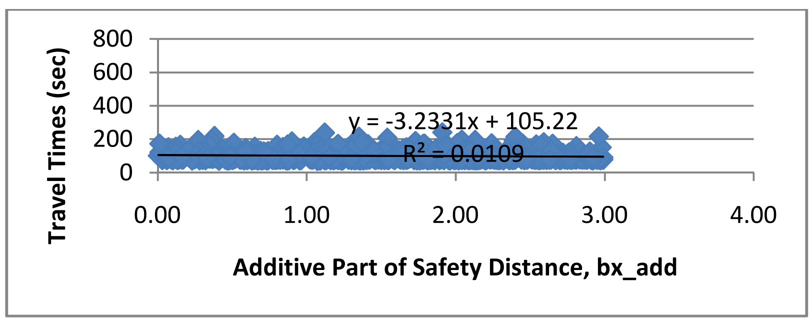
(b) Travel Time Segment #2



(c) Travel Time Segment #3

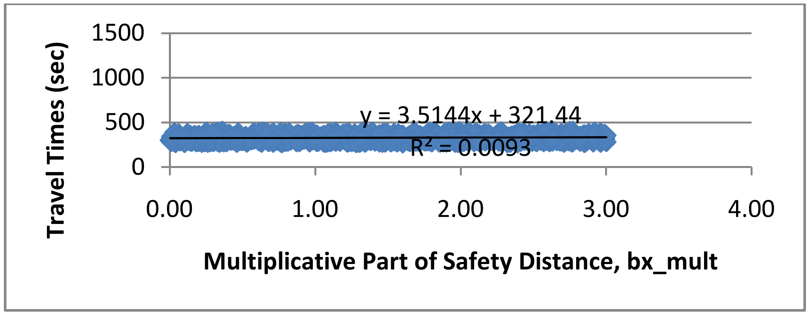


(d) Travel Time Segment #4

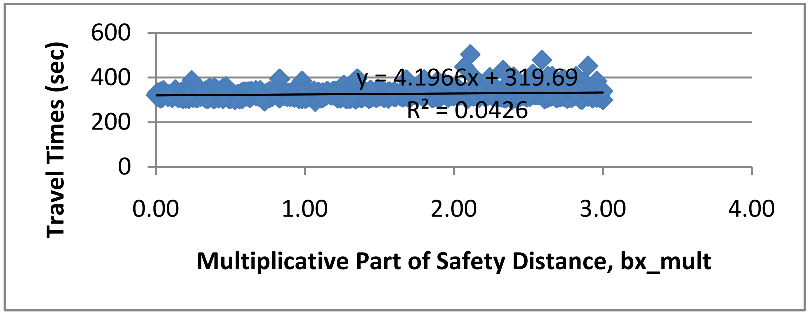


(e) Travel Time Segment #5

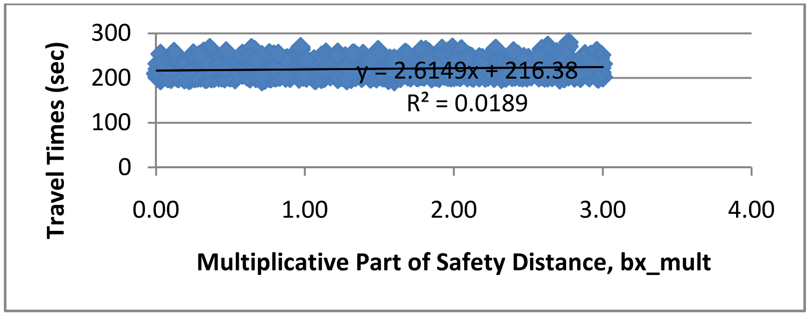
Figure 50(a-e): 100% Volume Scenario, Iteration #2, Parameter #6 Scatter Plots



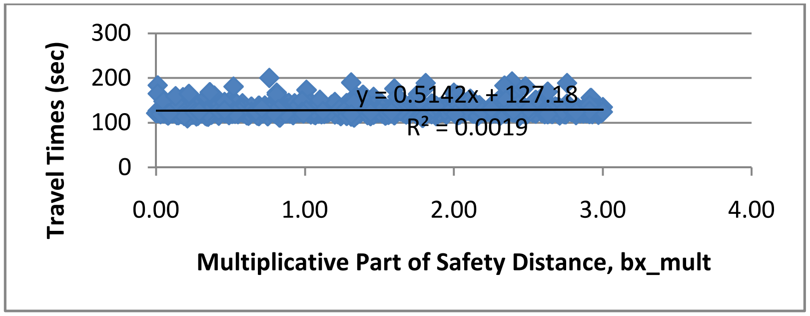
(a) Travel Time Segment #1



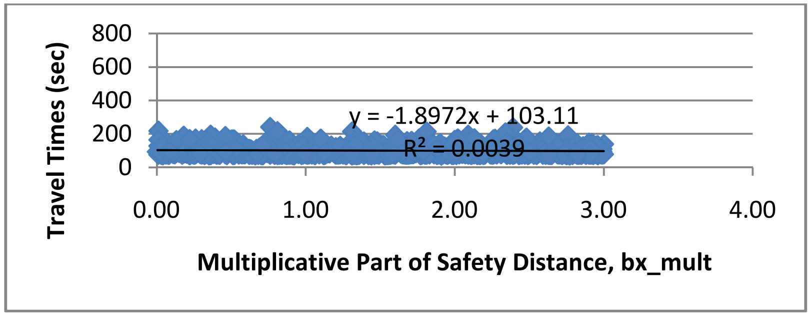
(b) Travel Time Segment #2



(c) Travel Time Segment #3

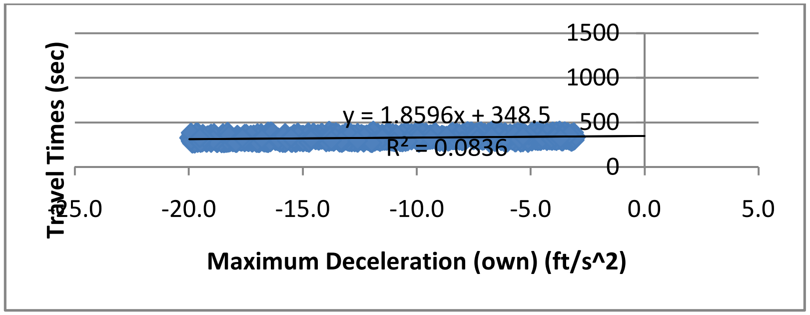


(d) Travel Time Segment #4

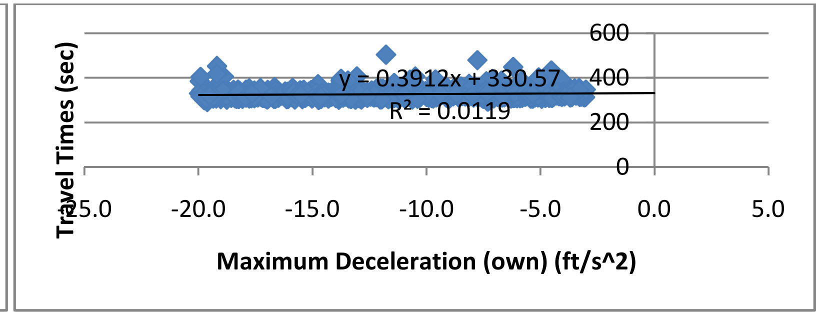


(e) Travel Time Segment #5

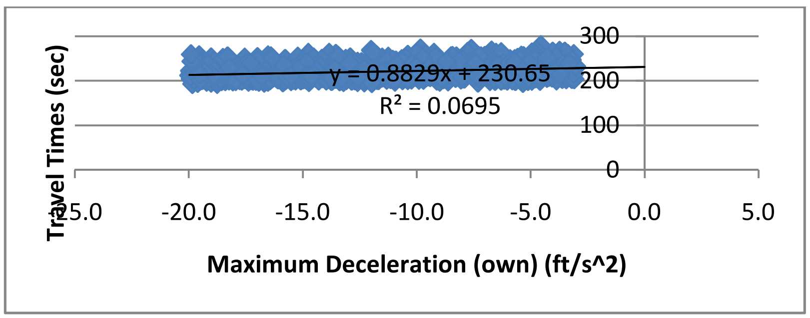
Figure 51(a-e): 100% Volume Scenario, Iteration #2, Parameter #7 Scatter Plots



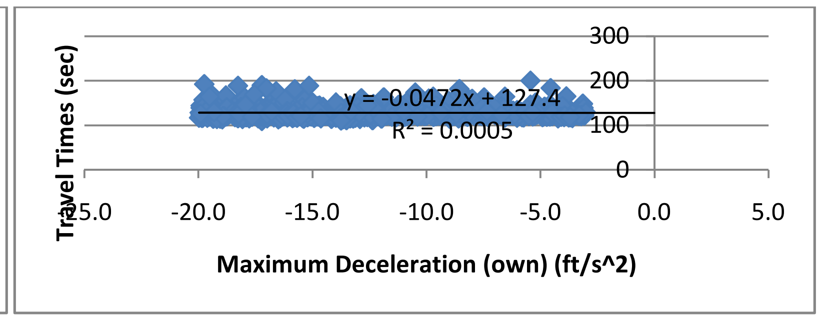
(a) Travel Time Segment #1



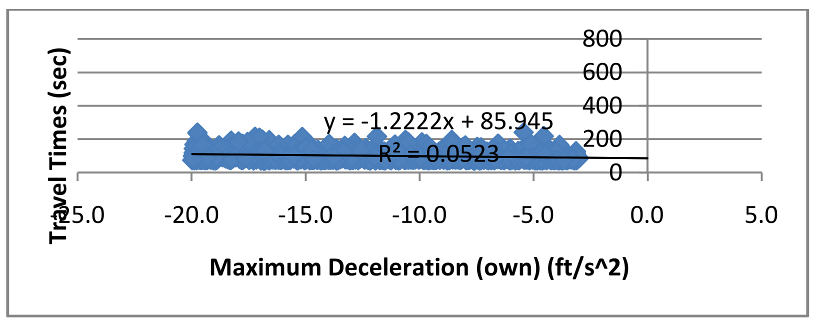
(b) Travel Time Segment #2



(c) Travel Time Segment #3

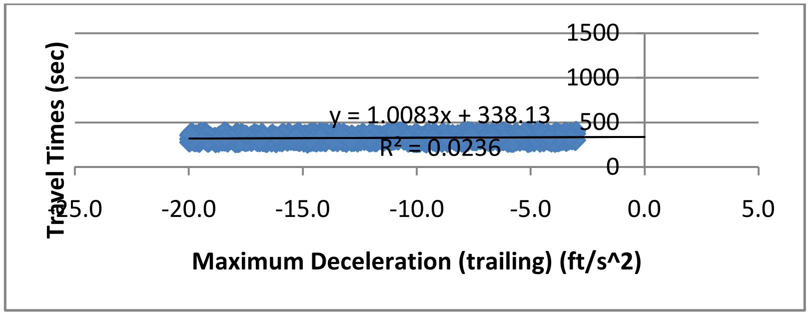


(d) Travel Time Segment #4

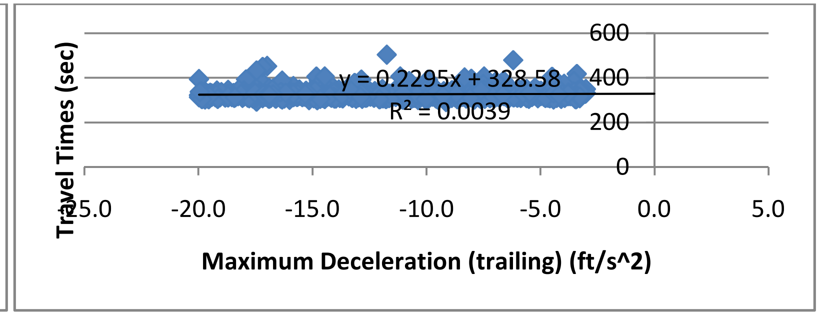


(e) Travel Time Segment #5

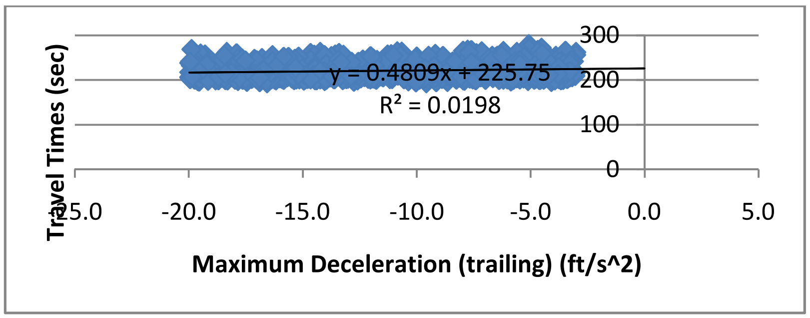
Figure 52(a-e): 100% Volume Scenario, Iteration #2, Parameter #8 Scatter Plots



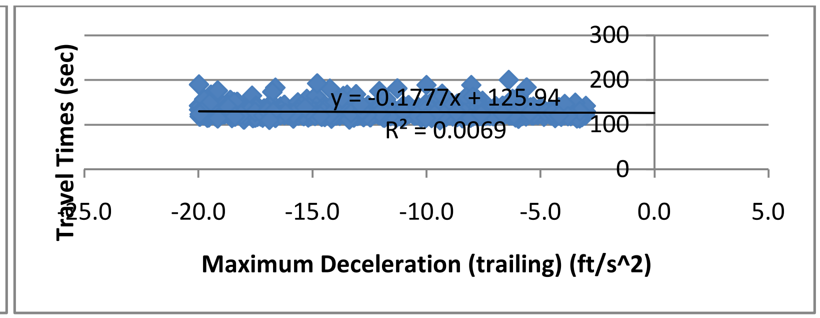
(a) Travel Time Segment #1



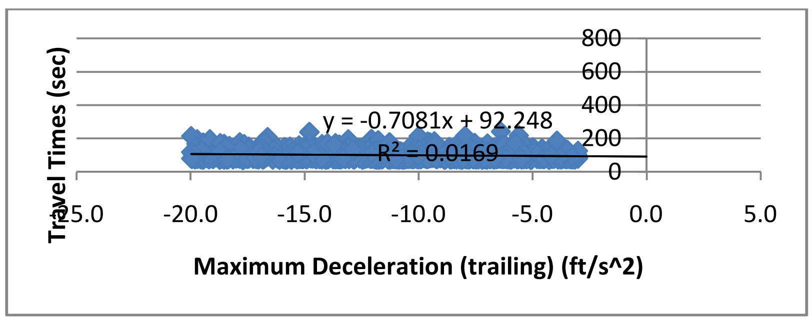
(b) Travel Time Segment #2



(c) Travel Time Segment #3

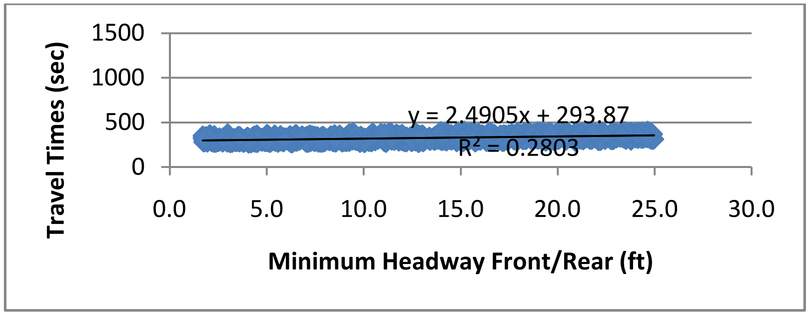


(d) Travel Time Segment #4

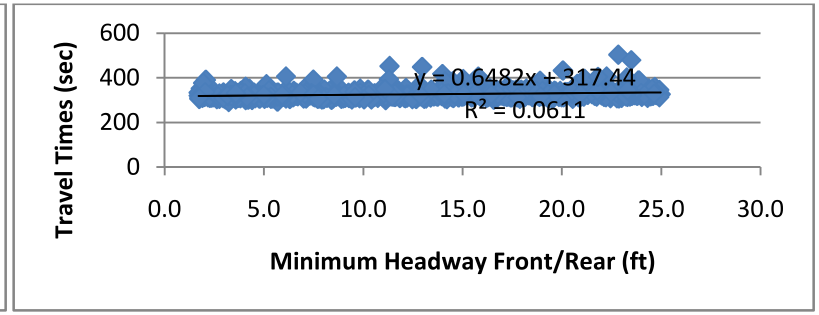


(e) Travel Time Segment #5

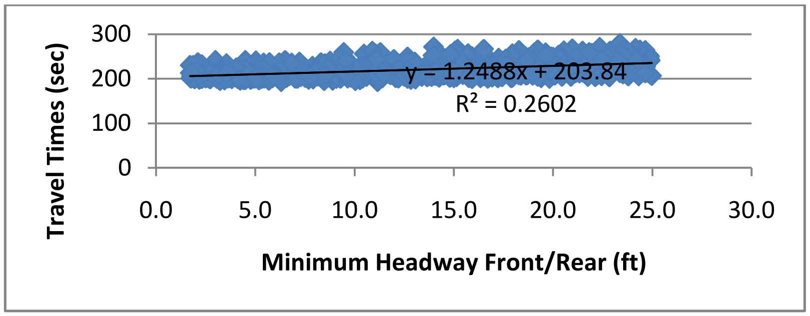
Figure 53(a-e): 100% Volume Scenario, Iteration #2, Parameter #9 Scatter Plots



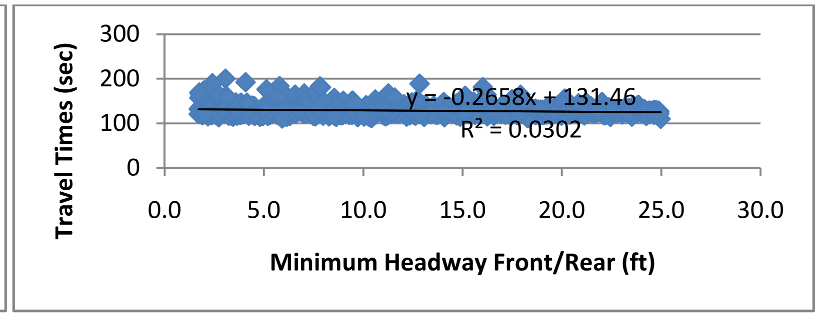
(a) Travel Time Segment #1



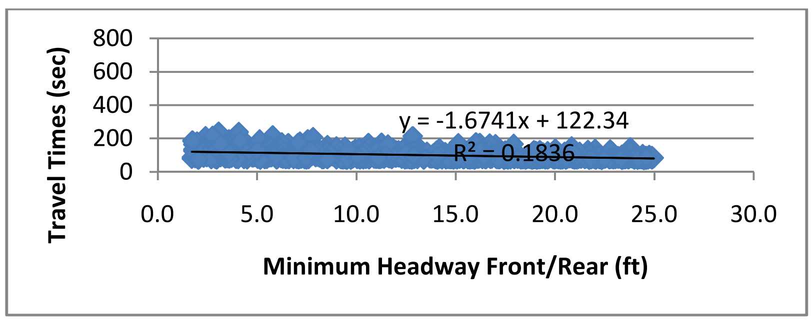
(b) Travel Time Segment #2



(c) Travel Time Segment #3

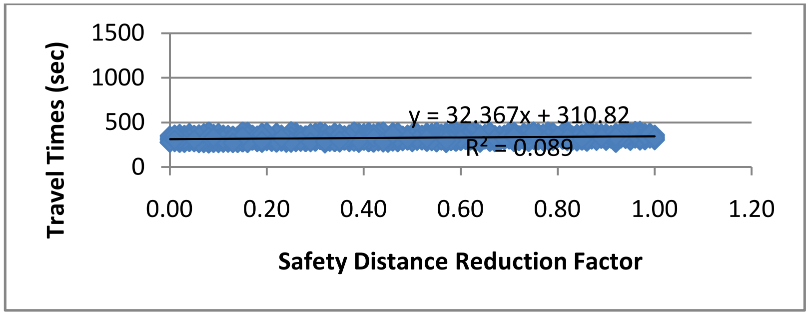


(d) Travel Time Segment #4

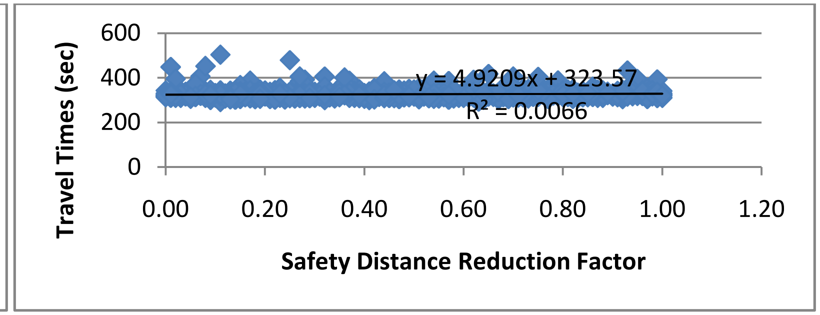


(e) Travel Time Segment #5

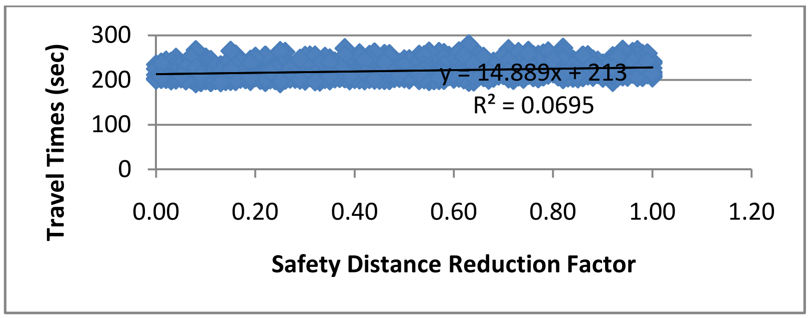
Figure 54(a-e): 100% Volume Scenario, Iteration #2, Parameter #15 Scatter Plots



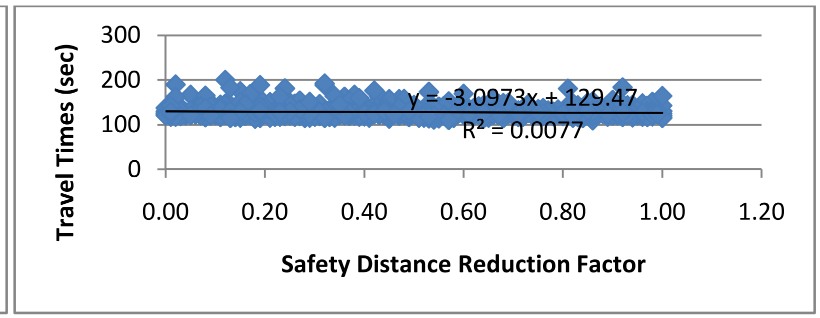
(a) Travel Time Segment #1



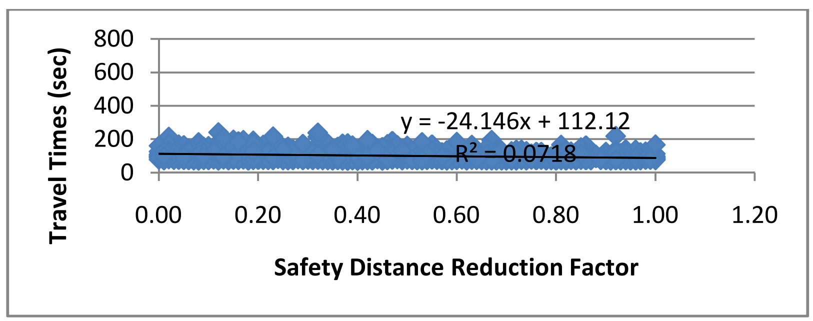
(b) Travel Time Segment #2



(c) Travel Time Segment #3

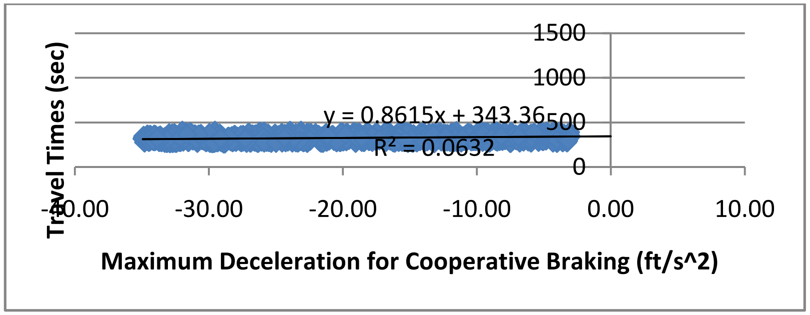


(d) Travel Time Segment #4

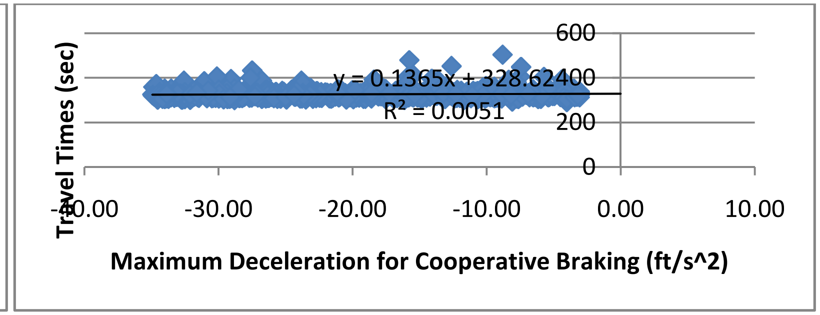


(e) Travel Time Segment #5

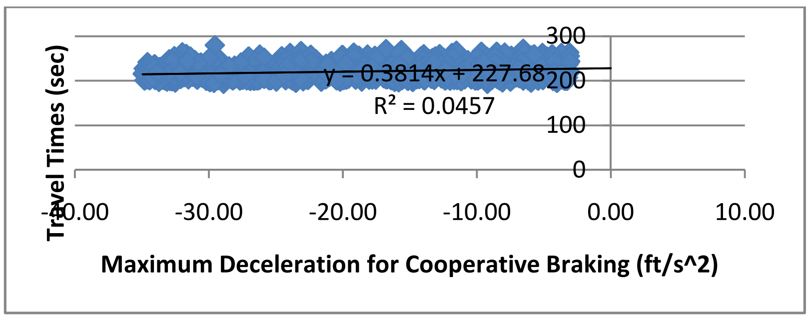
Figure 55(a-e): 100% Volume Scenario, Iteration #2, Parameter #16 Scatter Plots



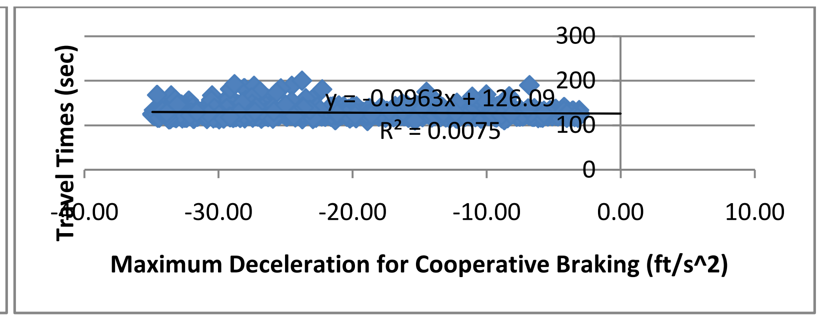
(a) Travel Time Segment #1



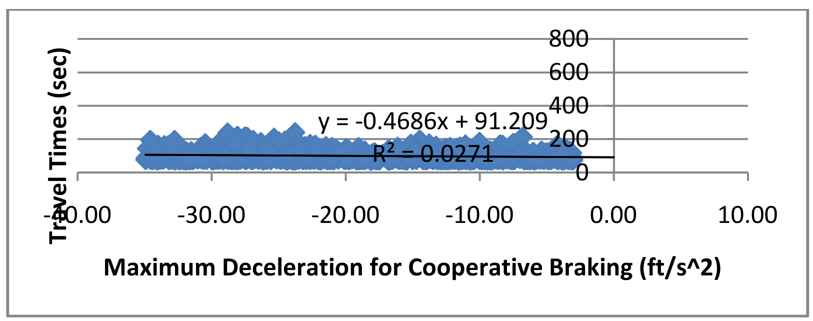
(b) Travel Time Segment #2



(c) Travel Time Segment #3

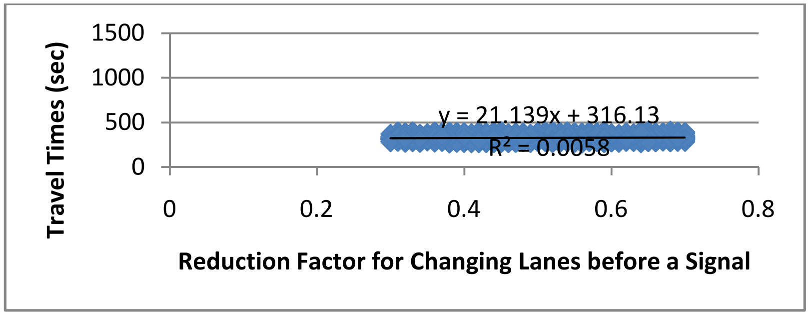


(d) Travel Time Segment #4

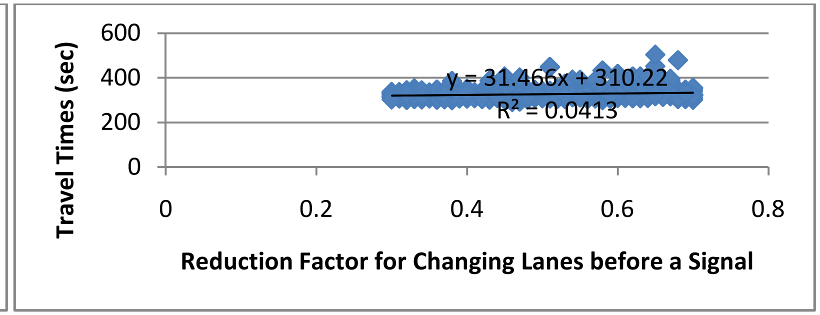


(e) Travel Time Segment #5

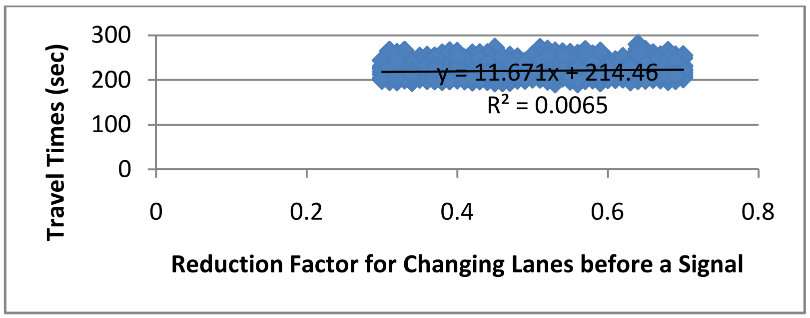
Figure 56(a-e): 100% Volume Scenario, Iteration #2, Parameter #17 Scatter Plots



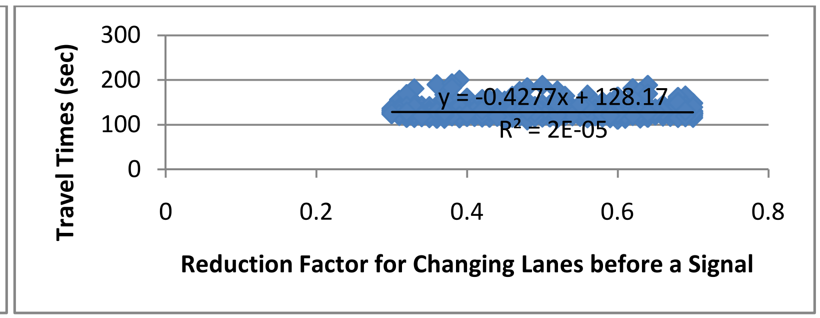
(a) Travel Time Segment #1



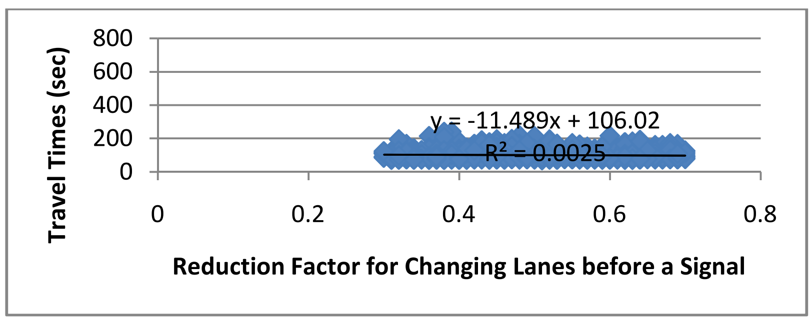
(b) Travel Time Segment #2



(c) Travel Time Segment #3

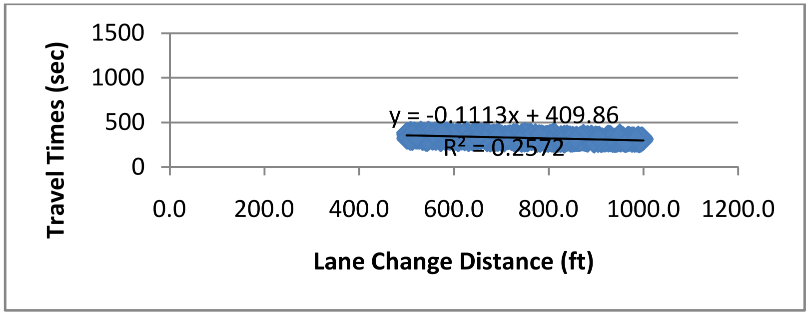


(d) Travel Time Segment #4

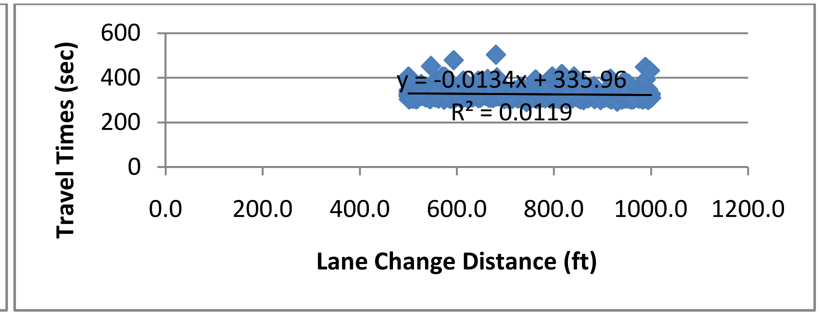


(e) Travel Time Segment #5

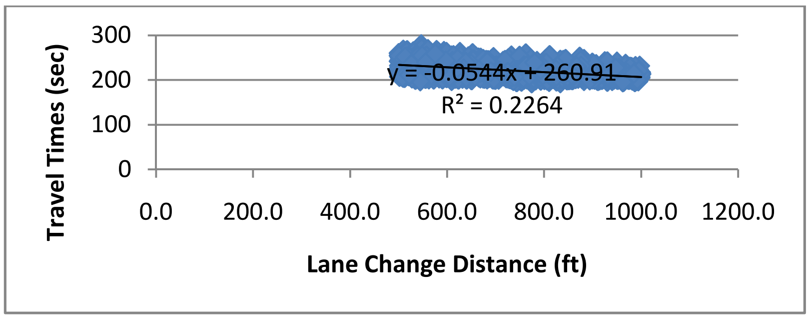
Figure 57(a-e): 100% Volume Scenario, Iteration #2, Parameter #18 Scatter Plots



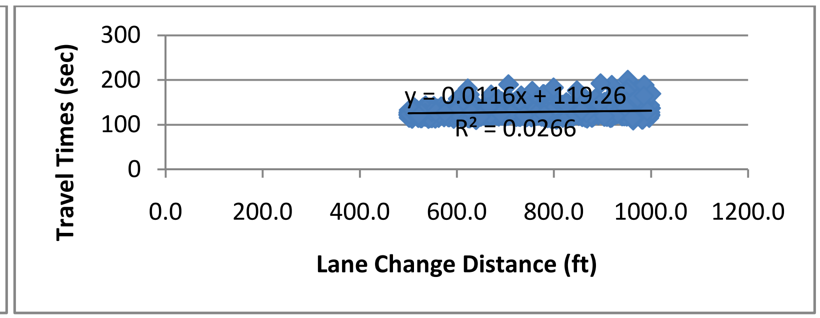
(a) Travel Time Segment #1



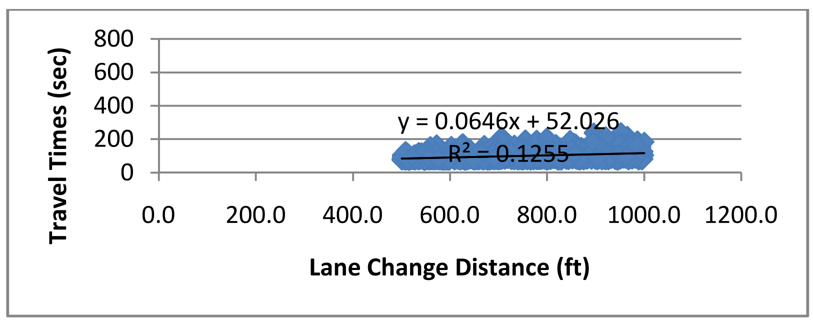
(b) Travel Time Segment #2



(c) Travel Time Segment #3

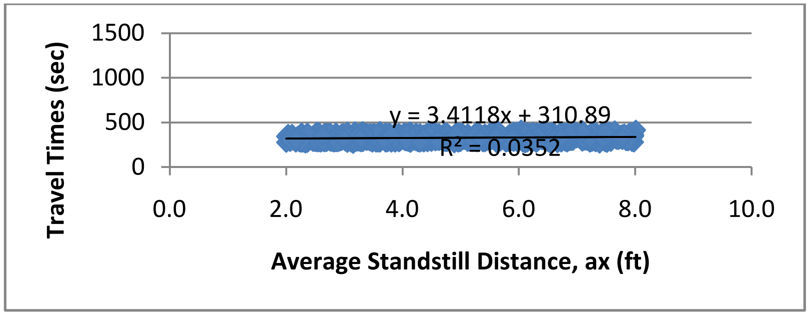


(d) Travel Time Segment #4

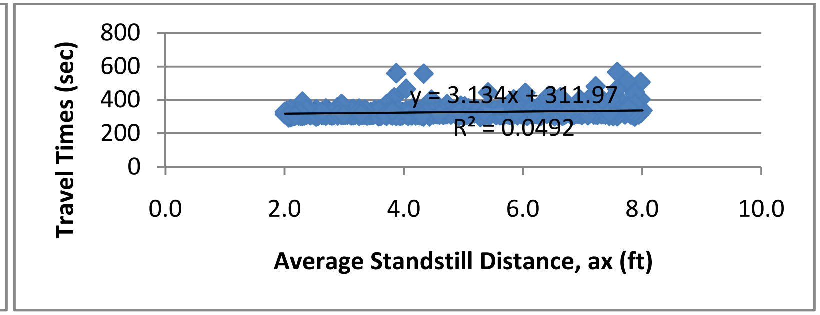


(e) Travel Time Segment #5

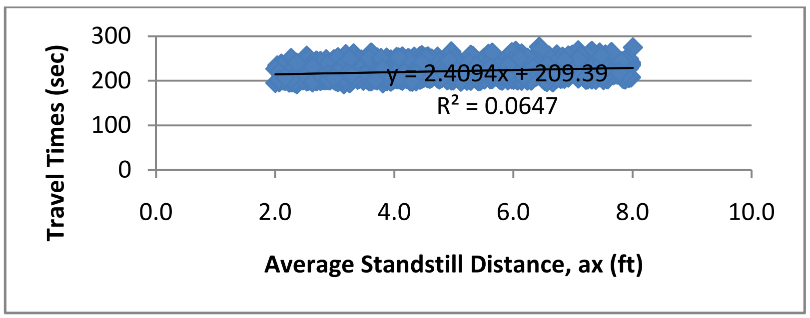
Figure 58(a-e): 100% Volume Scenario, Iteration #2, Parameter #22 Scatter Plots



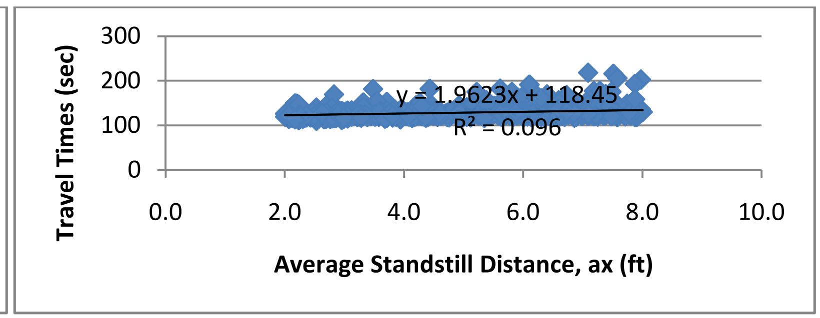
(a) Travel Time Segment #1



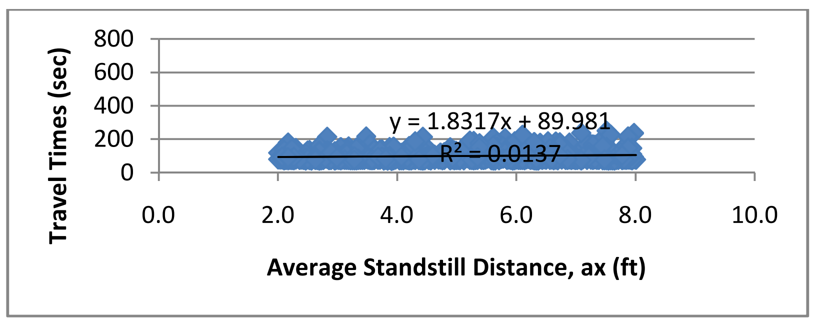
(b) Travel Time Segment #2



(c) Travel Time Segment #3

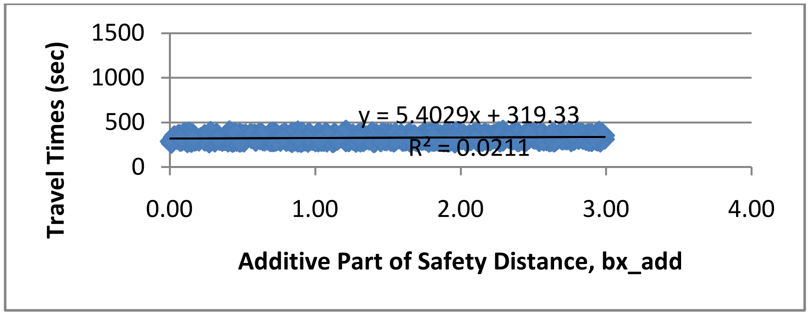


(d) Travel Time Segment #4

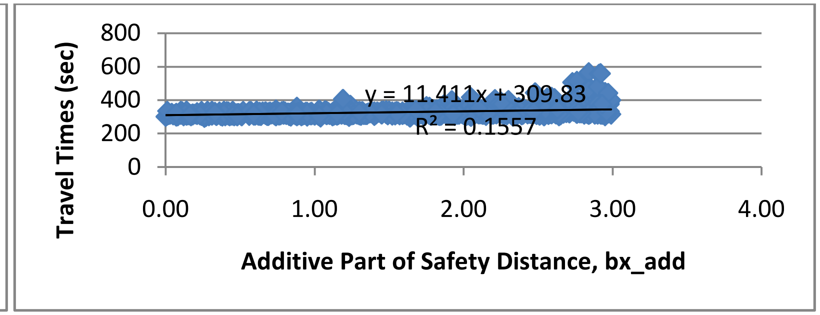


(e) Travel Time Segment #5

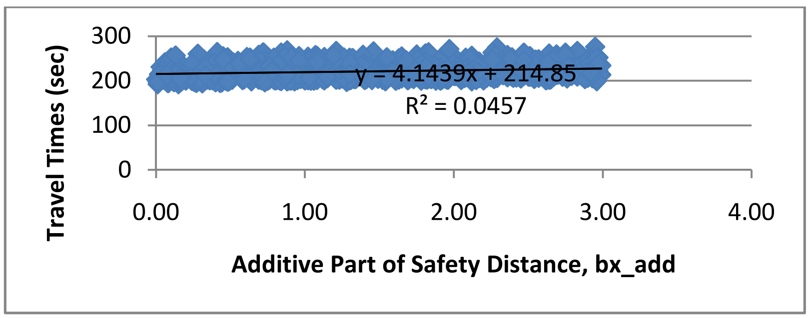
Figure 59(a-e): 100% Volume Scenario, Iteration #3, Parameter #5 Scatter Plots



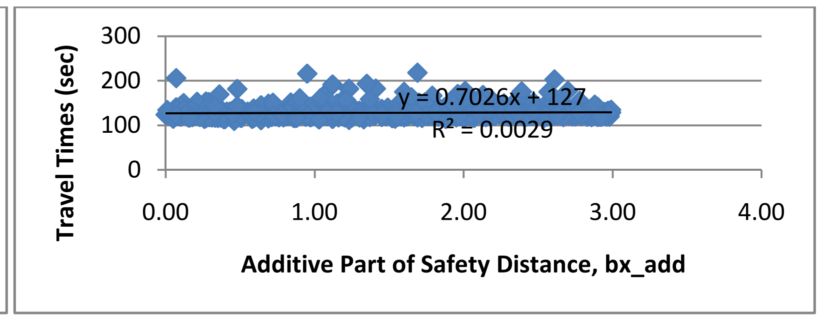
(a) Travel Time Segment #1



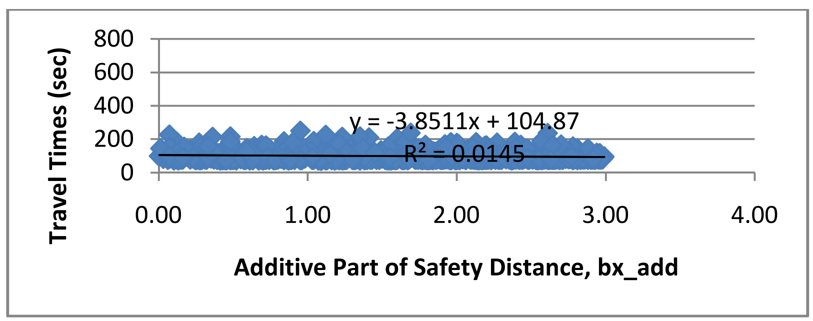
(b) Travel Time Segment #2



(c) Travel Time Segment #3

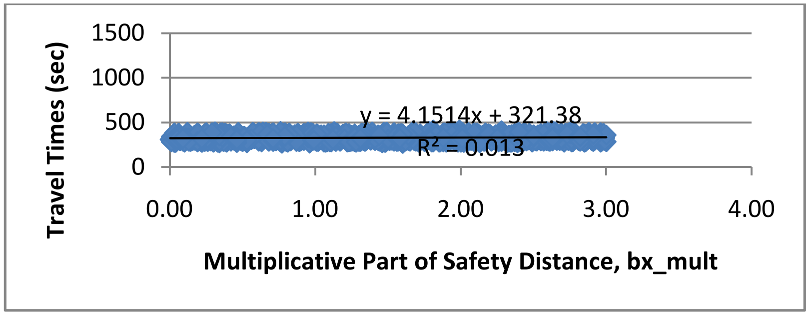


(d) Travel Time Segment #4

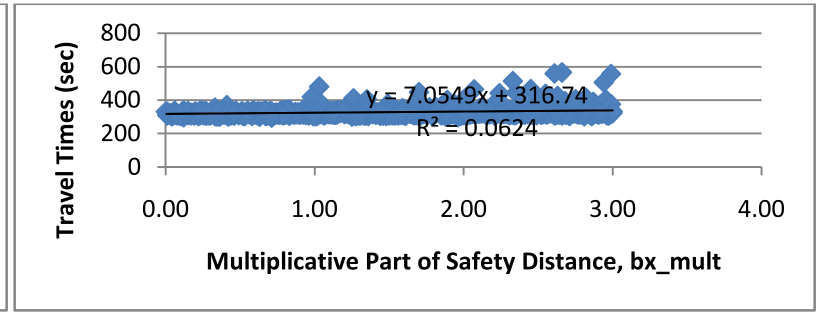


(e) Travel Time Segment #5

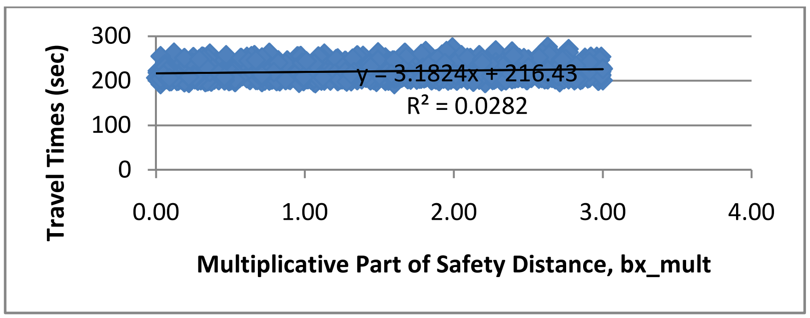
Figure 60(a-e): 100% Volume Scenario, Iteration #3, Parameter #6 Scatter Plots



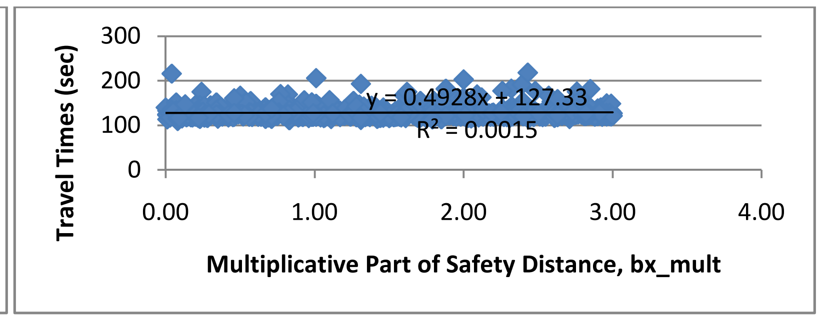
(a) Travel Time Segment #1



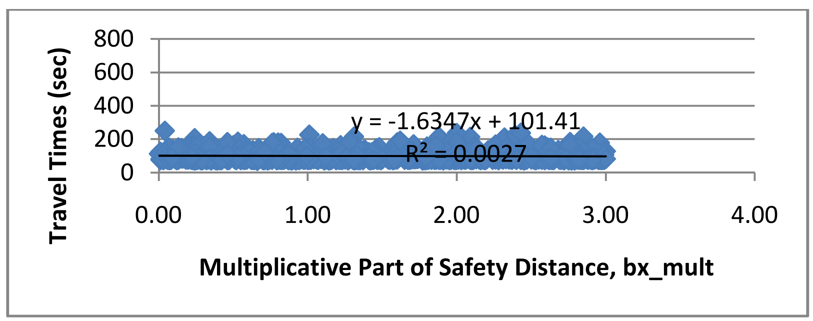
(b) Travel Time Segment #2



(c) Travel Time Segment #3

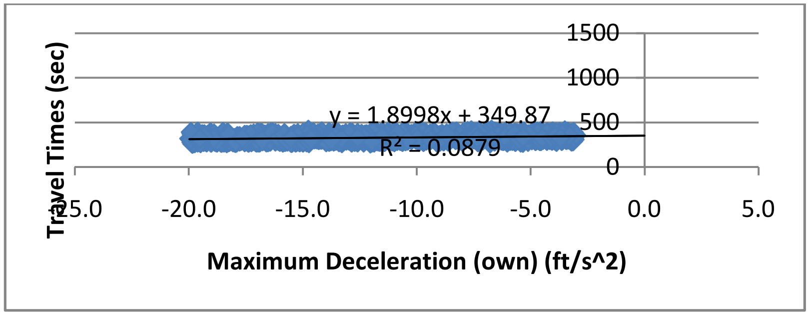


(d) Travel Time Segment #4

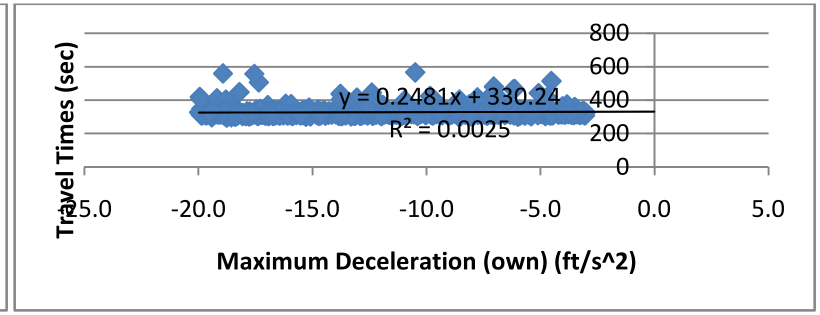


(e) Travel Time Segment #5

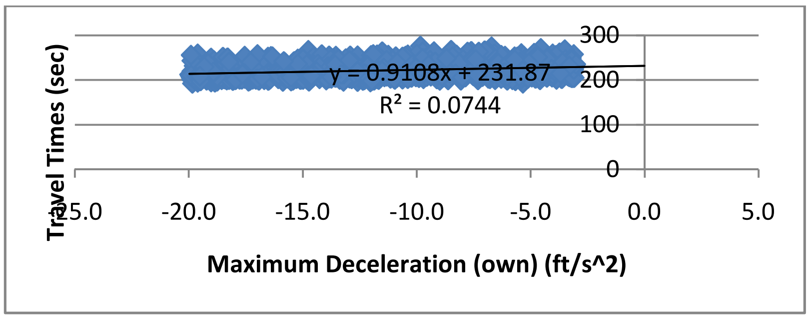
Figure 61(a-e): 100% Volume Scenario, Iteration #3, Parameter #7 Scatter Plots



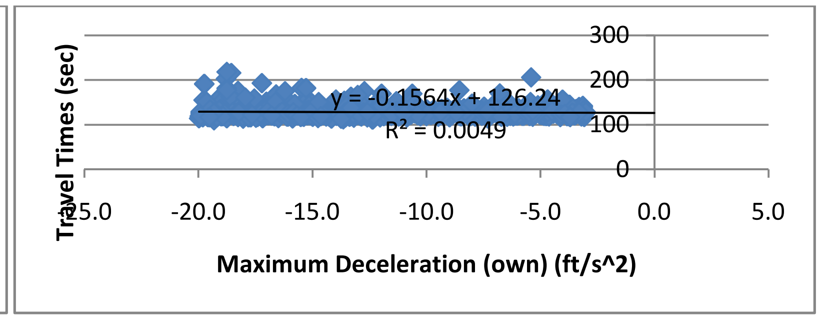
(a) Travel Time Segment #1



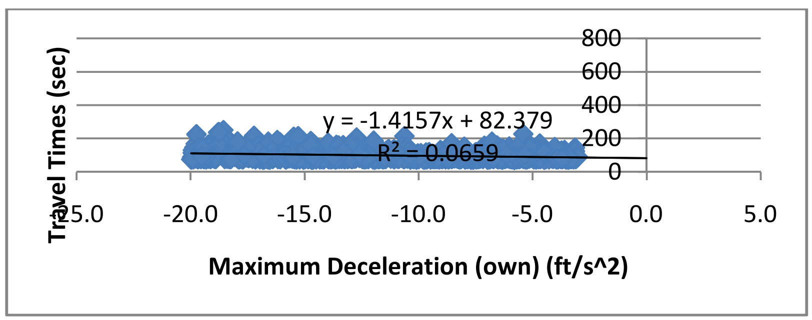
(b) Travel Time Segment #2



(c) Travel Time Segment #3

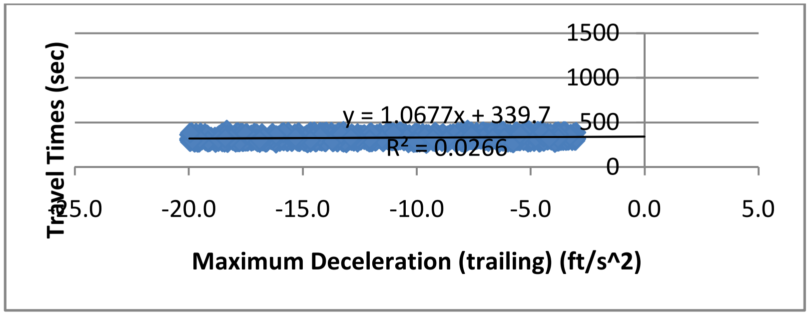


(d) Travel Time Segment #4

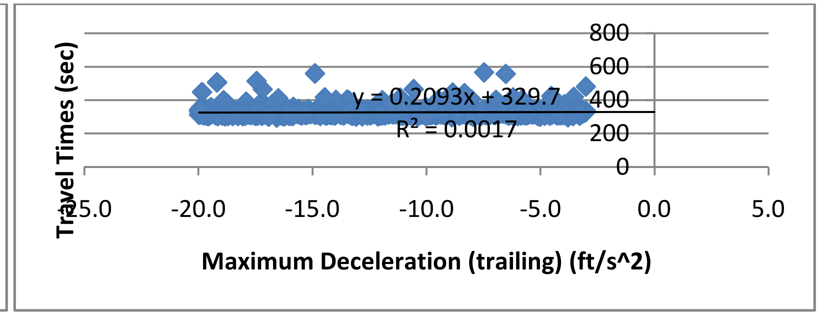


(e) Travel Time Segment #5

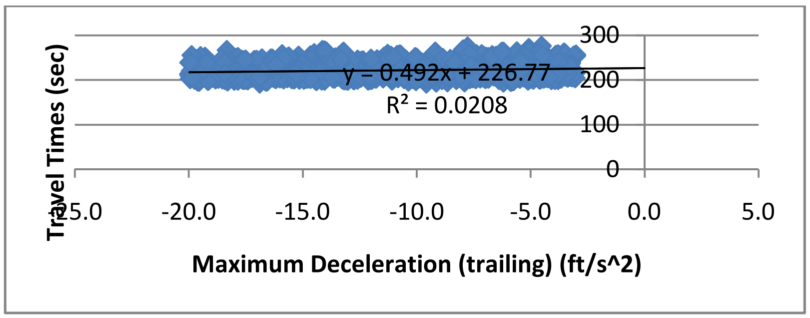
Figure 62(a-e): 100% Volume Scenario, Iteration #3, Parameter #8 Scatter Plots



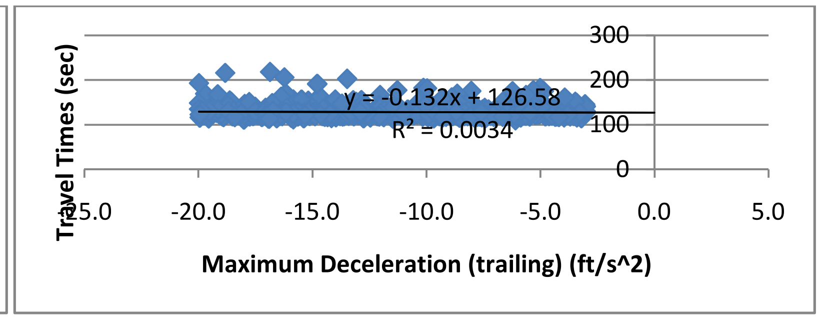
(a) Travel Time Segment #1



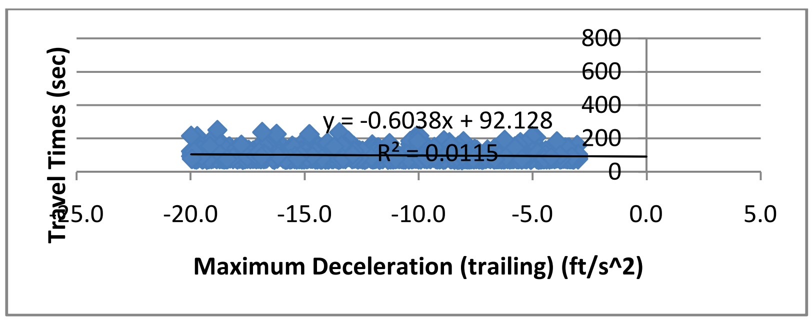
(b) Travel Time Segment #2



(c) Travel Time Segment #3

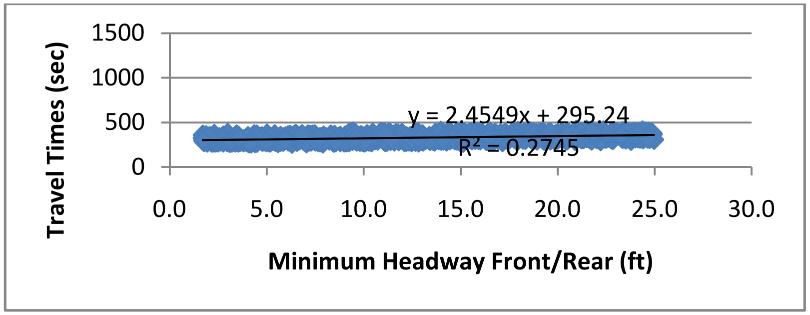


(d) Travel Time Segment #4

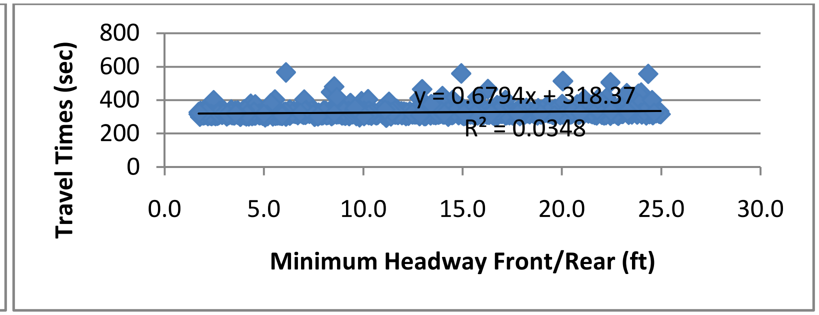


(e) Travel Time Segment #5

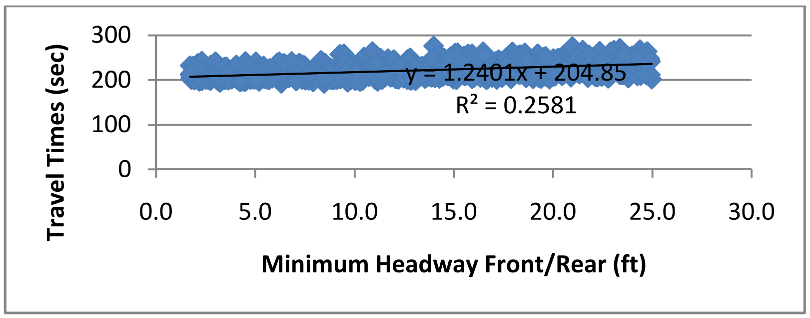
Figure 63(a-e): 100% Volume Scenario, Iteration #3, Parameter #9 Scatter Plots



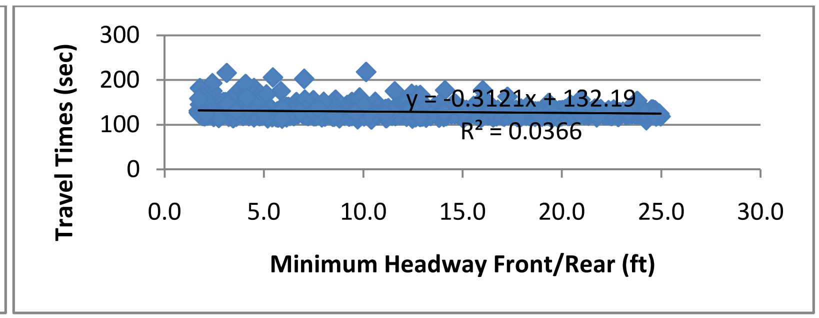
(a) Travel Time Segment #1



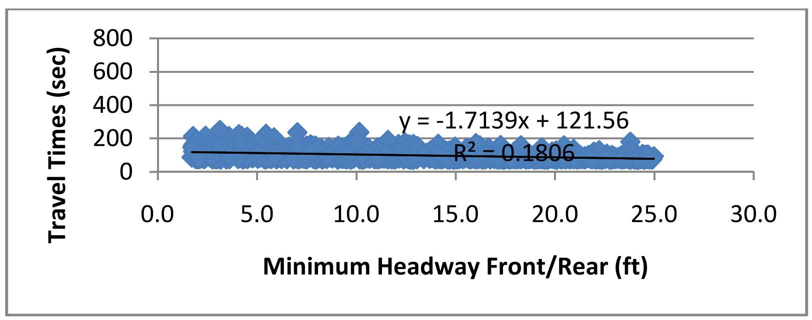
(b) Travel Time Segment #2



(c) Travel Time Segment #3

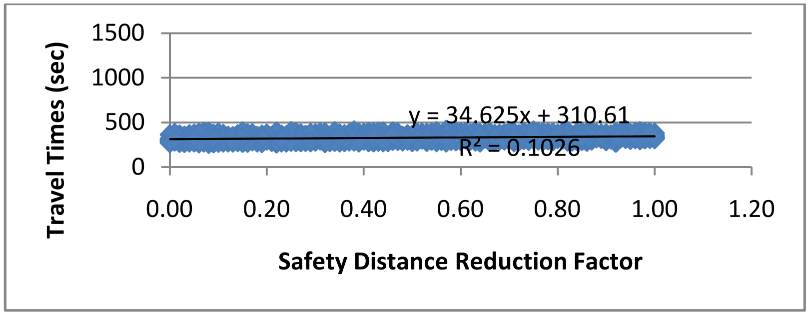


(d) Travel Time Segment #4

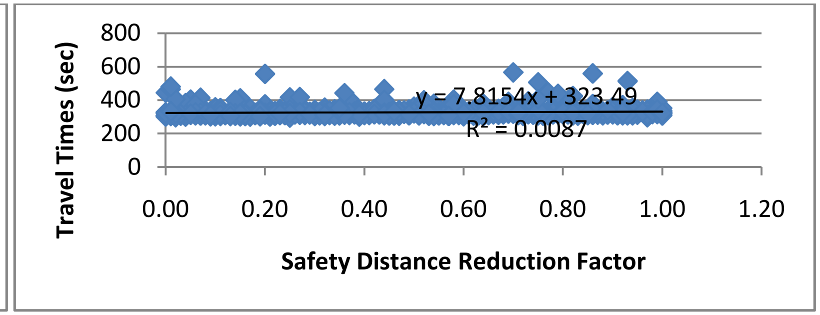


(e) Travel Time Segment #5

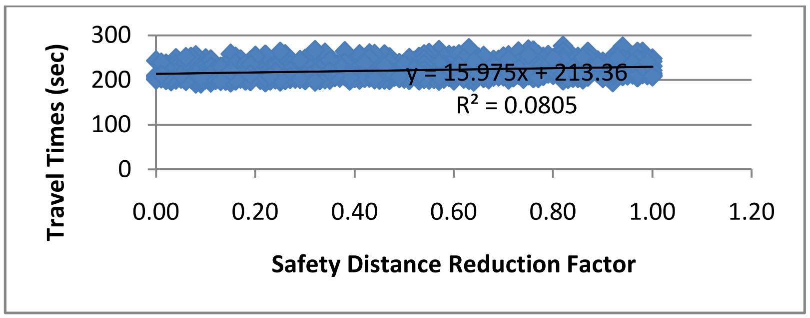
Figure 64(a-e): 100% Volume Scenario, Iteration #3, Parameter #15 Scatter Plots



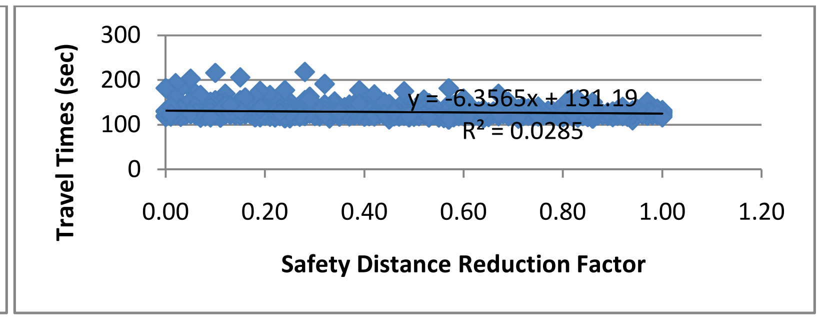
(a) Travel Time Segment #1



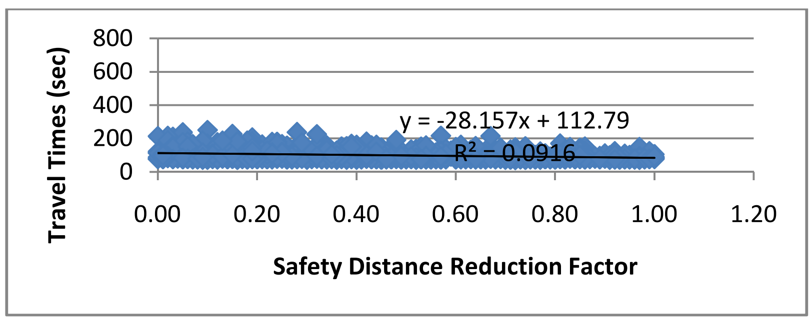
(b) Travel Time Segment #2



(c) Travel Time Segment #3

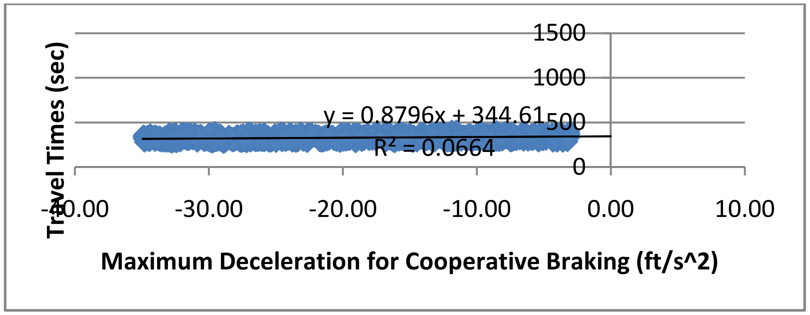


(d) Travel Time Segment #4

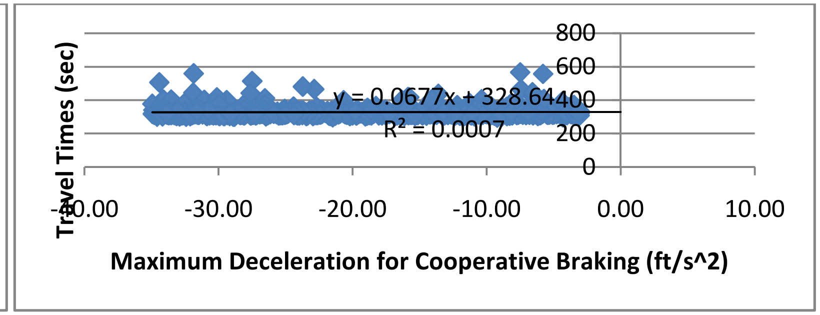


(e) Travel Time Segment #5

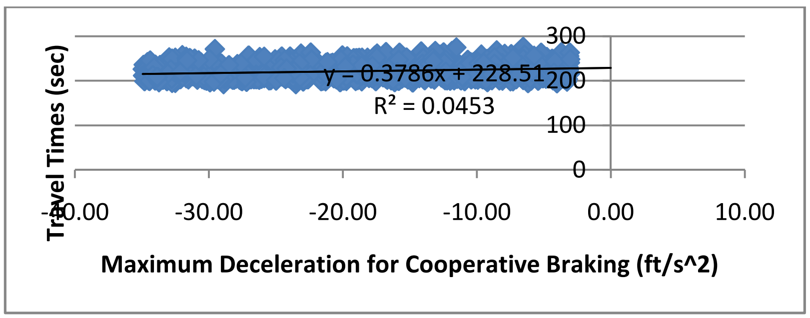
Figure 65(a-e): 100% Volume Scenario, Iteration #3, Parameter #16 Scatter Plots



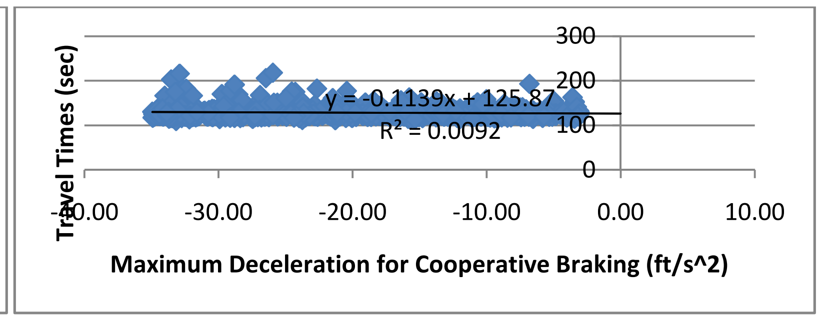
(a) Travel Time Segment #1



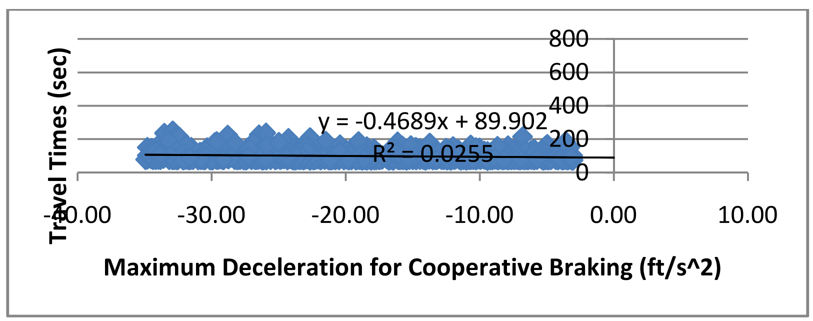
(b) Travel Time Segment #2



(c) Travel Time Segment #3

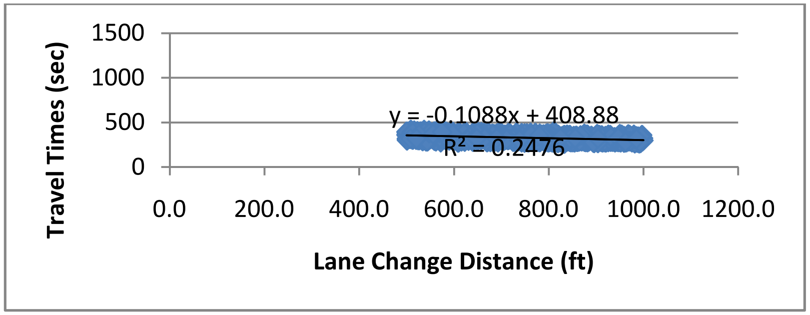


(d) Travel Time Segment #4

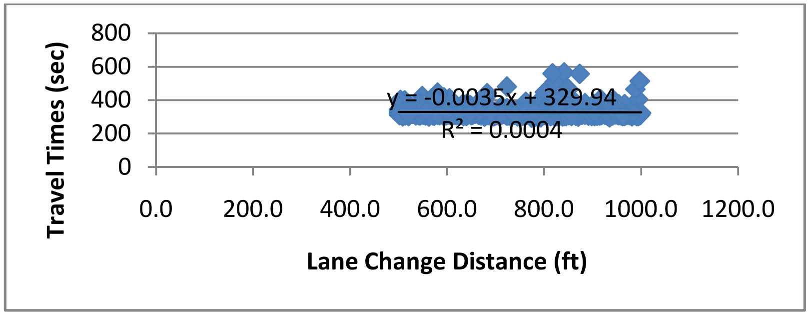


(e) Travel Time Segment #5

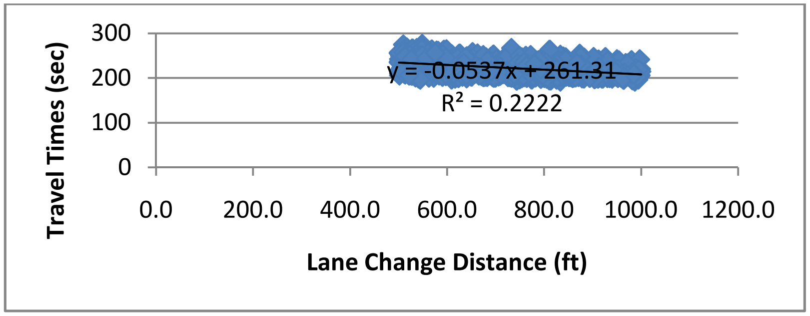
Figure 66(a-e): 100% Volume Scenario, Iteration #3, Parameter #17 Scatter Plots



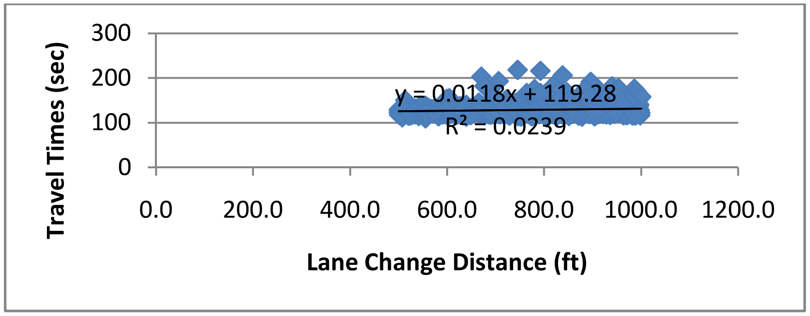
(a) Travel Time Segment #1



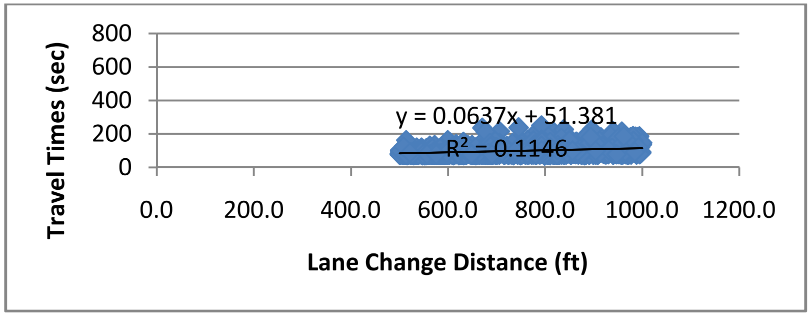
(b) Travel Time Segment #2



(c) Travel Time Segment #3



(d) Travel Time Segment #4

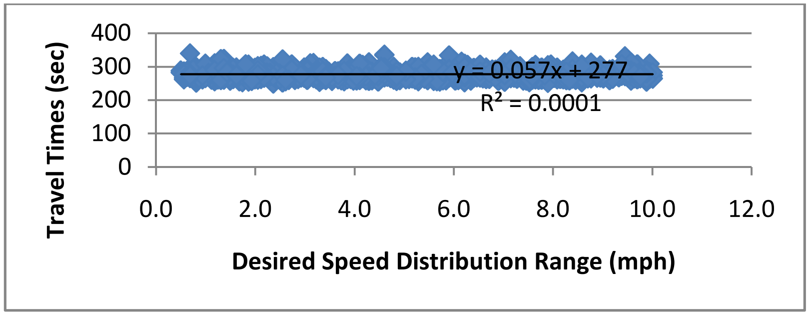


(e) Travel Time Segment #5

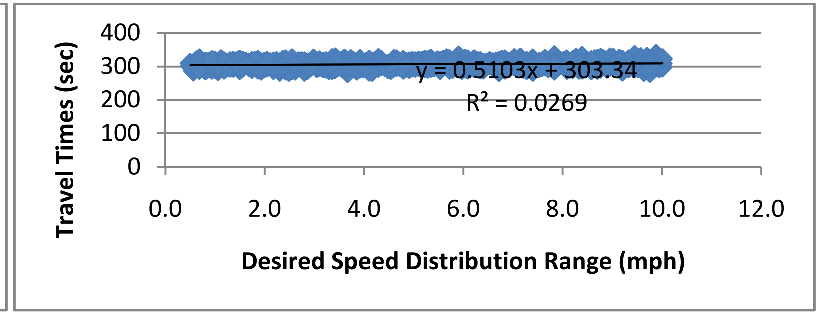
Figure 67(a-e): 100% Volume Scenario, Iteration #3, Parameter #22 Scatter Plots

APPENDIX B

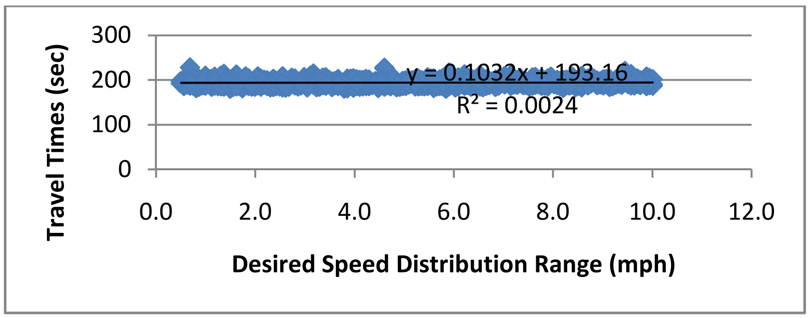
75% VOLUME SCENARIO RESULTS



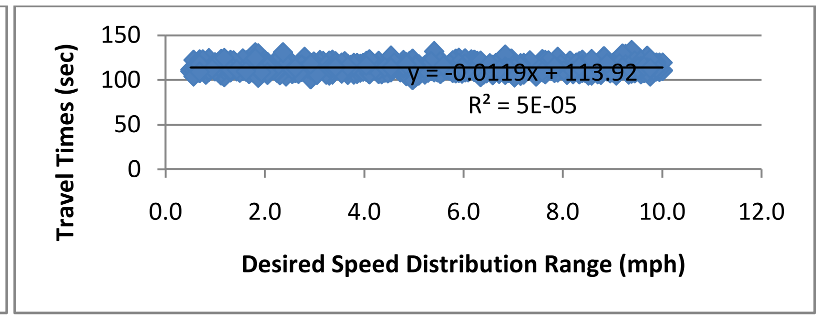
(a) Travel Time Segment #1



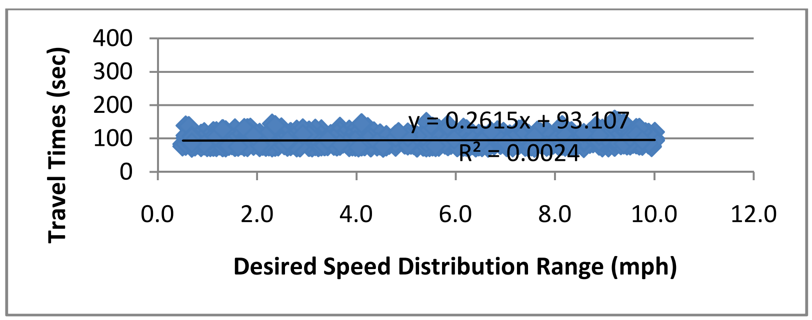
(b) Travel Time Segment #2



(c) Travel Time Segment #3

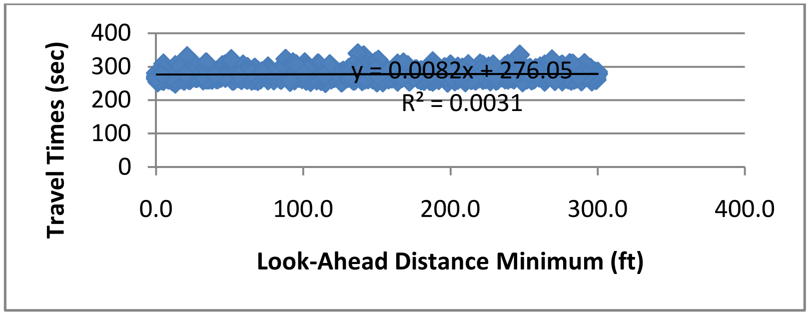


(d) Travel Time Segment #4

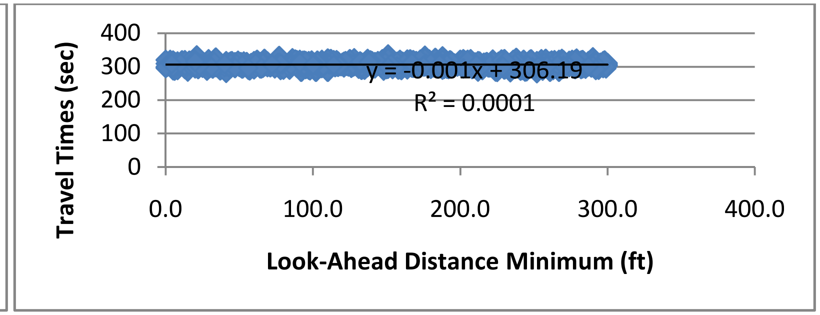


(e) Travel Time Segment #5

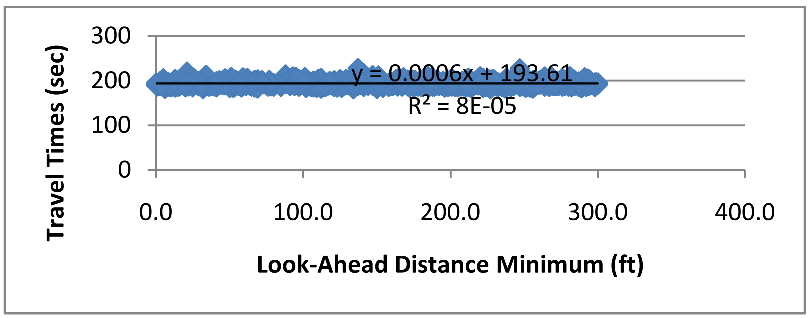
Figure 68(a-e): 75% Volume Scenario, Iteration #1, Parameter #1 Scatter Plots



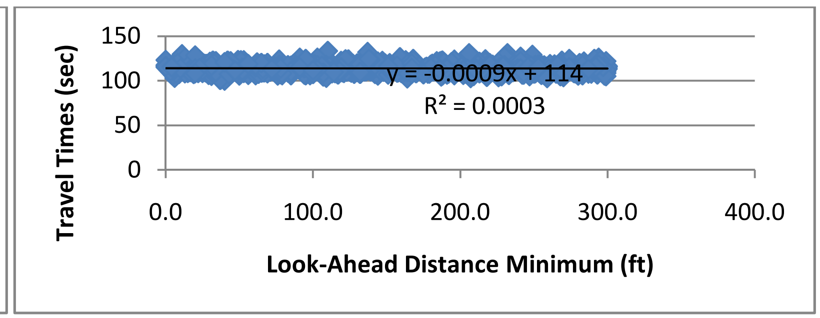
(a) Travel Time Segment #1



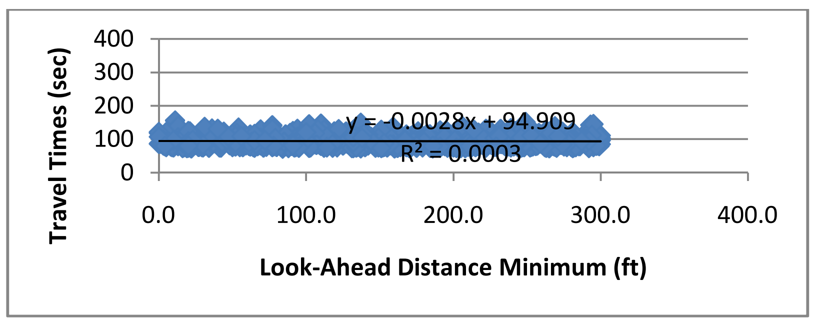
(b) Travel Time Segment #2



(c) Travel Time Segment #3

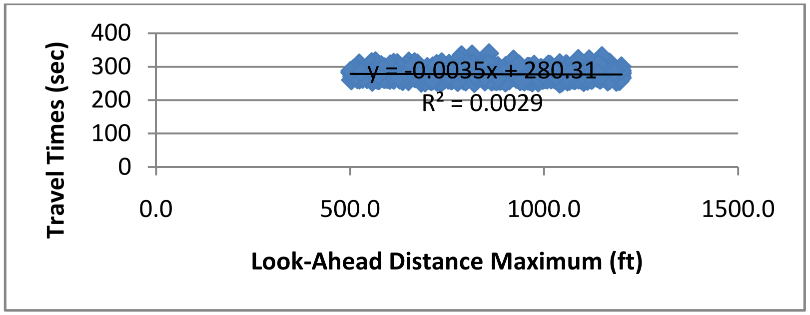


(d) Travel Time Segment #4

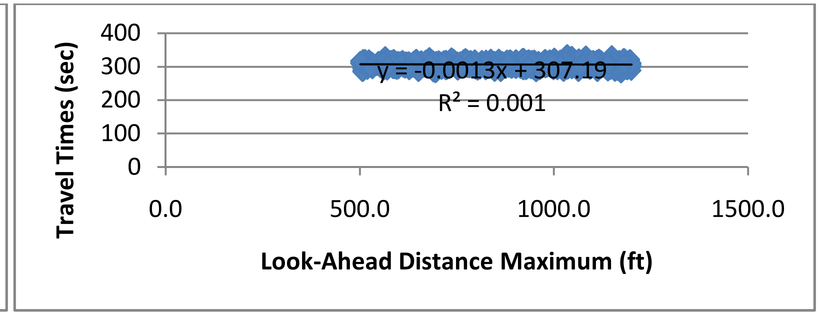


(e) Travel Time Segment #5

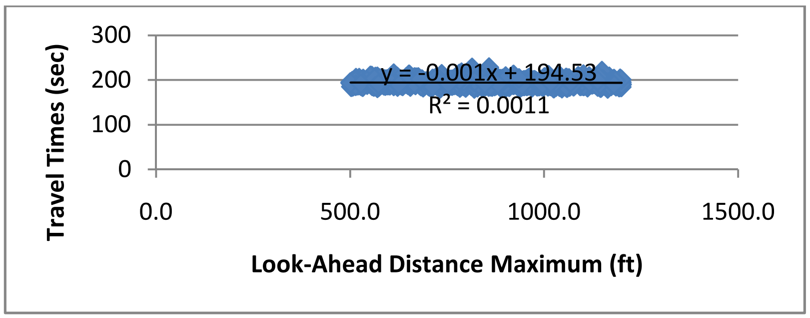
Figure 69(a-e): 75% Volume Scenario, Iteration #1, Parameter #2 Scatter Plots



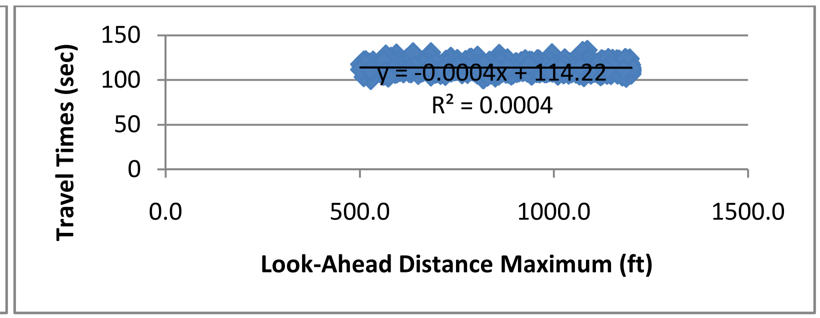
(a) Travel Time Segment #1



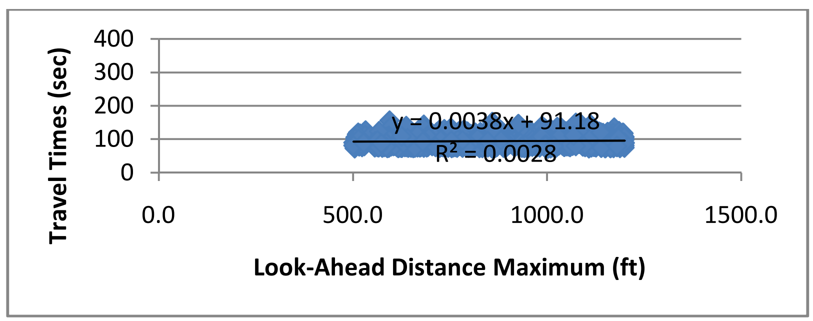
(b) Travel Time Segment #2



(c) Travel Time Segment #3

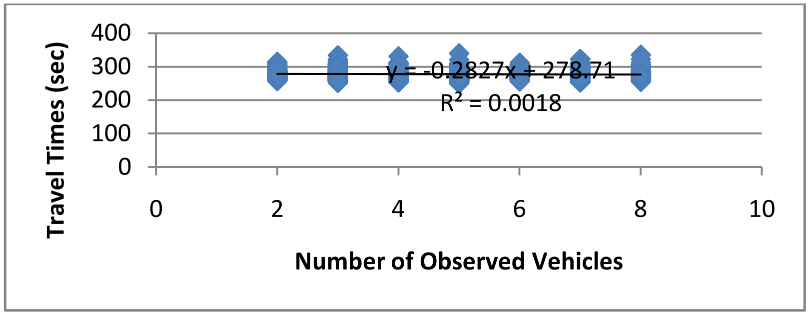


(d) Travel Time Segment #4

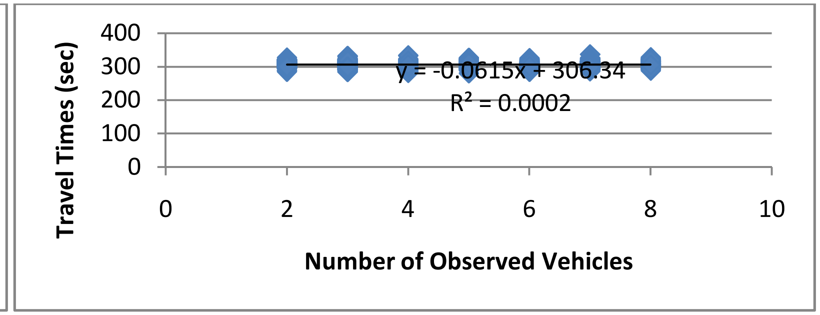


(e) Travel Time Segment #5

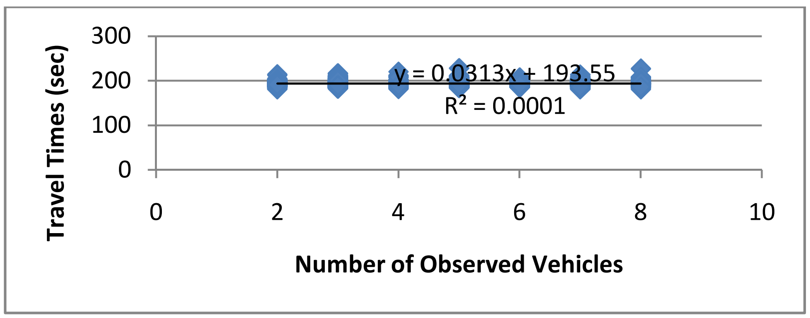
Figure 70(a-e): 75% Volume Scenario, Iteration #1, Parameter #3 Scatter Plots



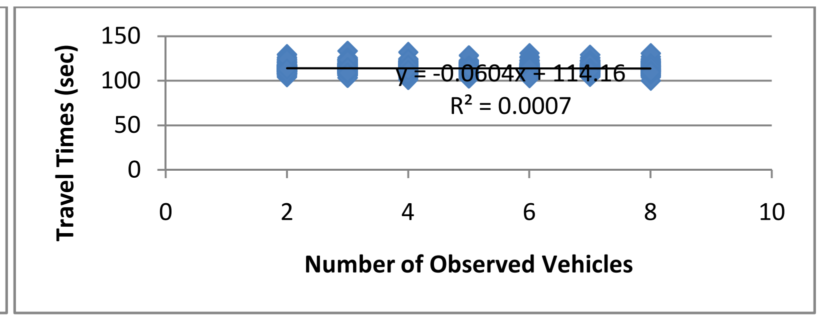
(a) Travel Time Segment #1



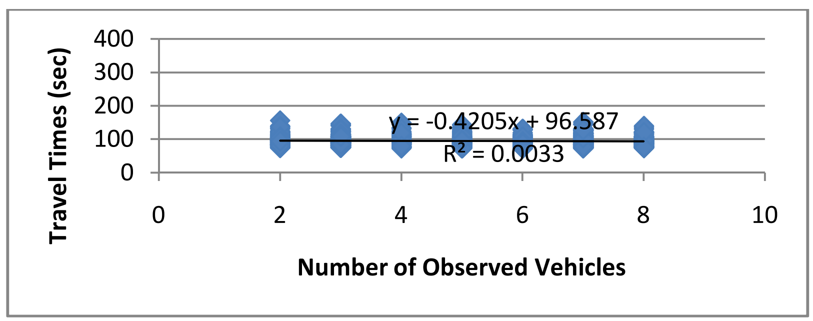
(b) Travel Time Segment #2



(c) Travel Time Segment #3

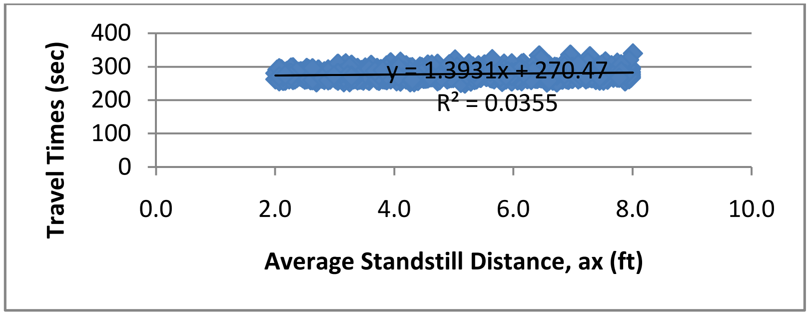


(d) Travel Time Segment #4

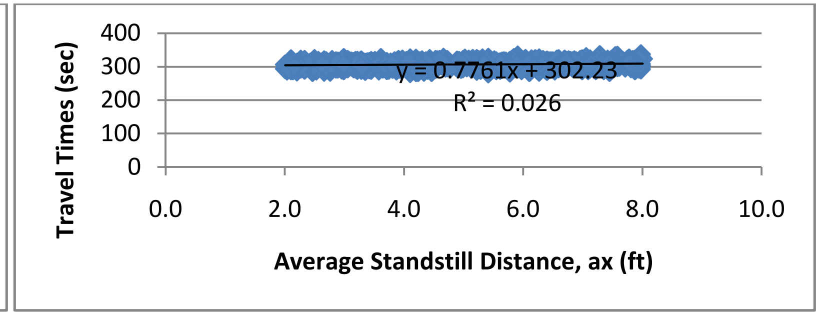


(e) Travel Time Segment #5

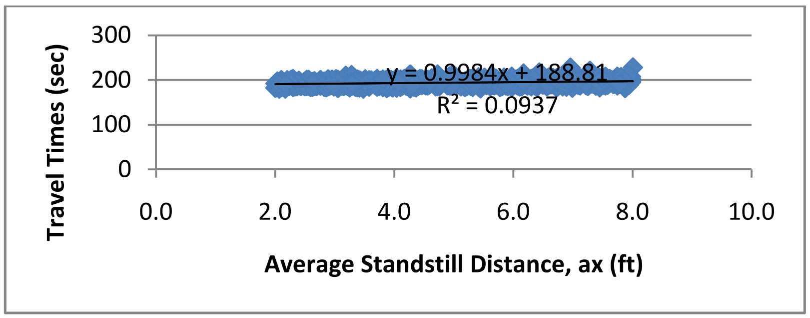
Figure 71(a-e): 75% Volume Scenario, Iteration #1, Parameter #4 Scatter Plots



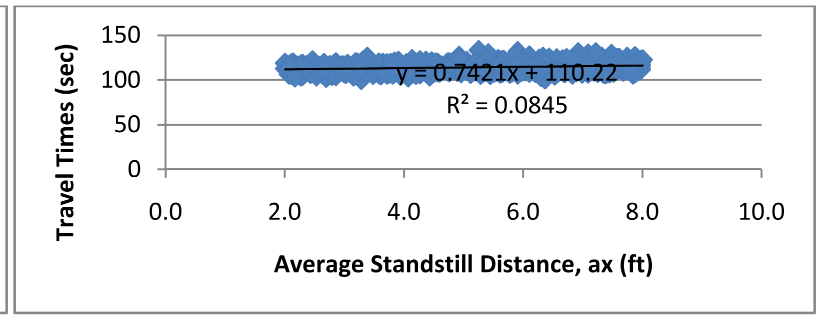
(a) Travel Time Segment #1



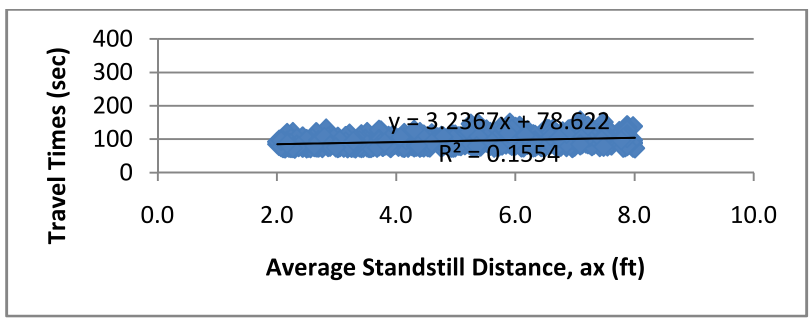
(b) Travel Time Segment #2



(c) Travel Time Segment #3

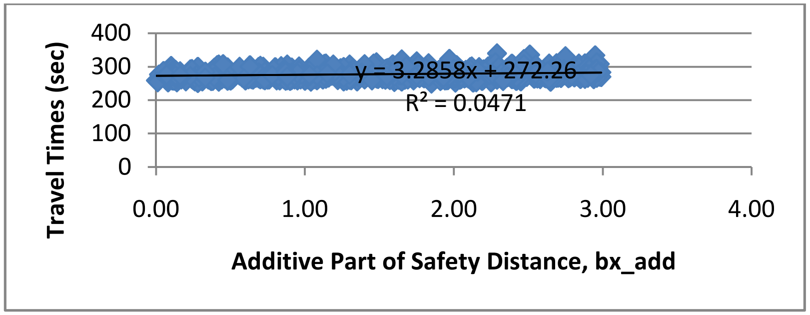


(d) Travel Time Segment #4

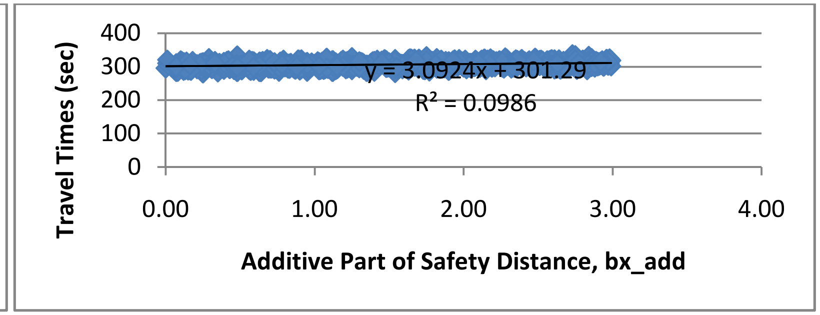


(e) Travel Time Segment #5

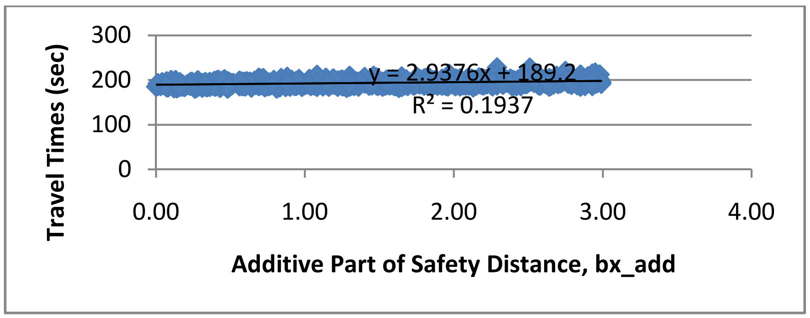
Figure 72(a-e): 75% Volume Scenario, Iteration #1, Parameter #5 Scatter Plots



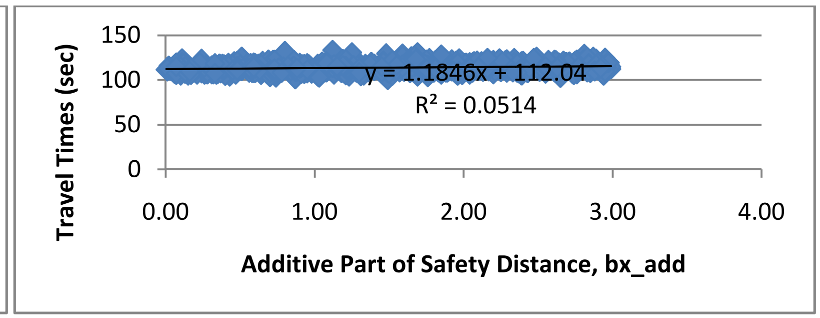
(a) Travel Time Segment #1



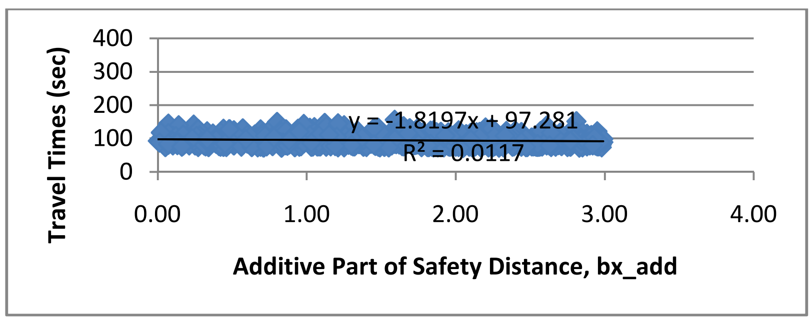
(b) Travel Time Segment #2



(c) Travel Time Segment #3

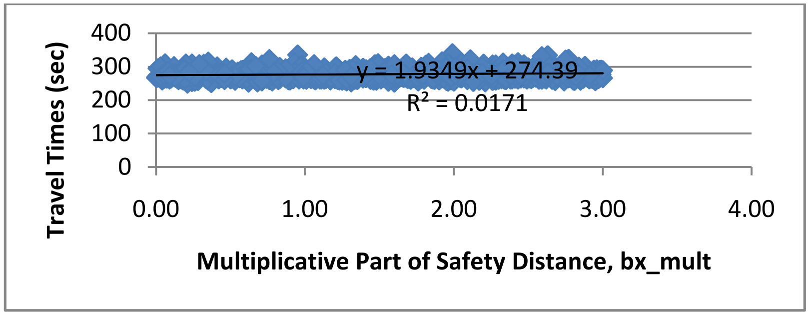


(d) Travel Time Segment #4

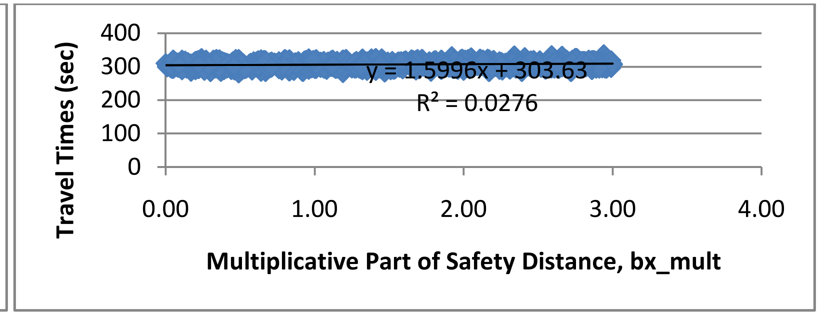


(e) Travel Time Segment #5

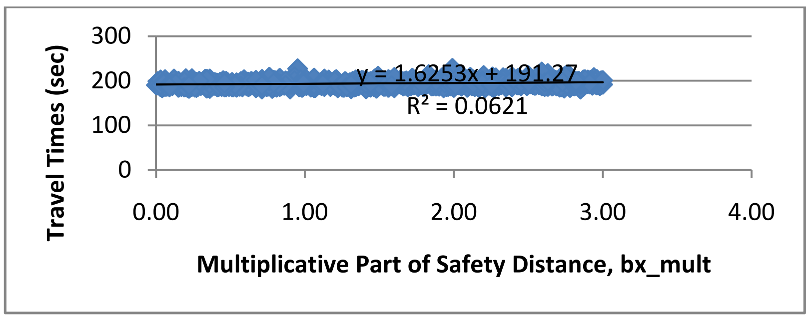
Figure 73(a-e): 75% Volume Scenario, Iteration #1, Parameter #6 Scatter Plots



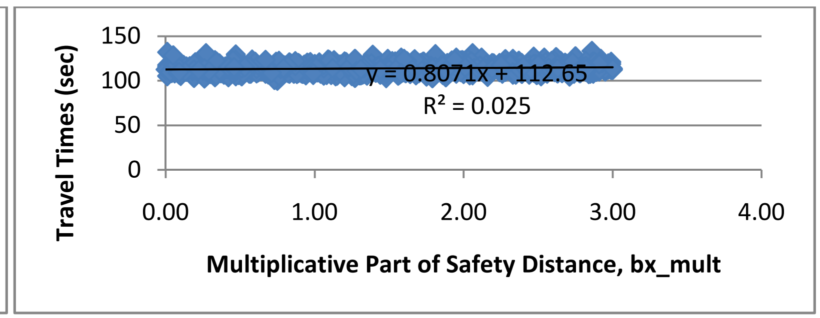
(a) Travel Time Segment #1



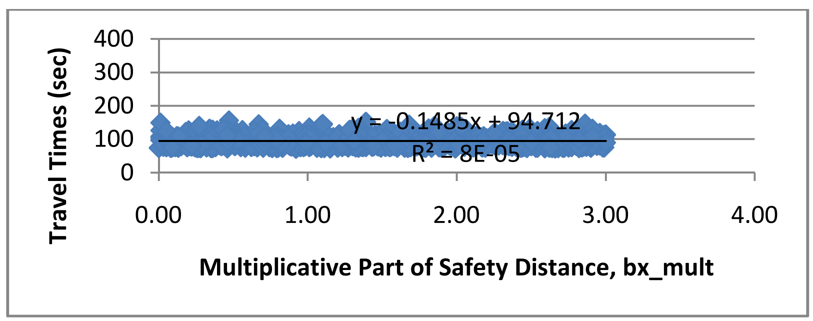
(b) Travel Time Segment #2



(c) Travel Time Segment #3

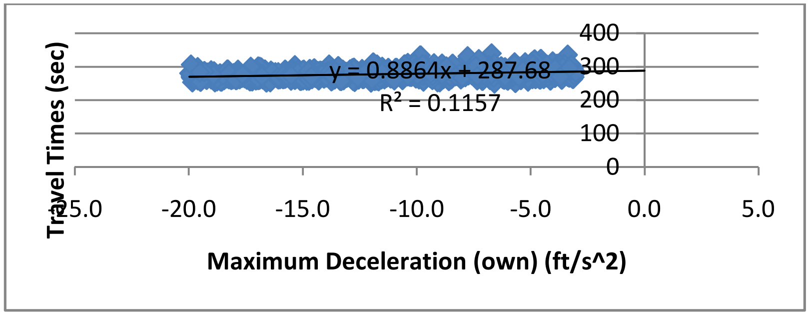


(d) Travel Time Segment #4

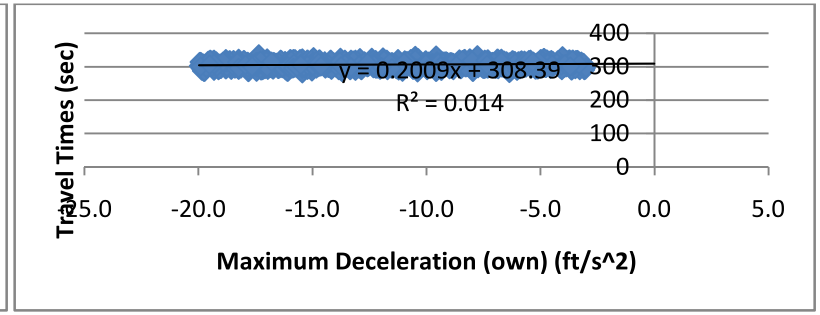


(e) Travel Time Segment #5

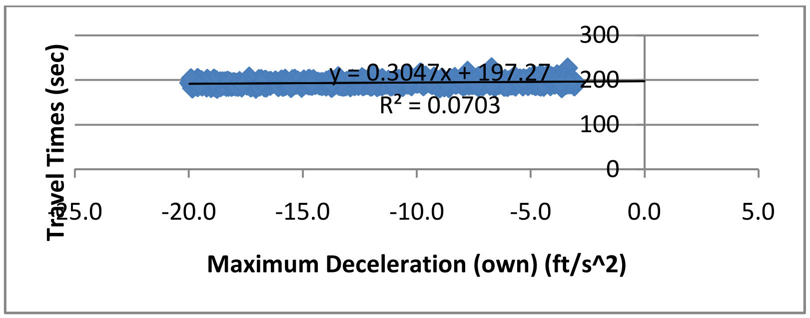
Figure 74(a-e): 75% Volume Scenario, Iteration #1, Parameter #7 Scatter Plots



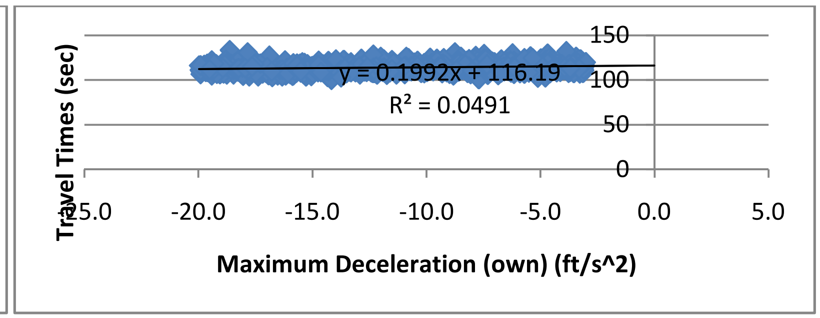
(a) Travel Time Segment #1



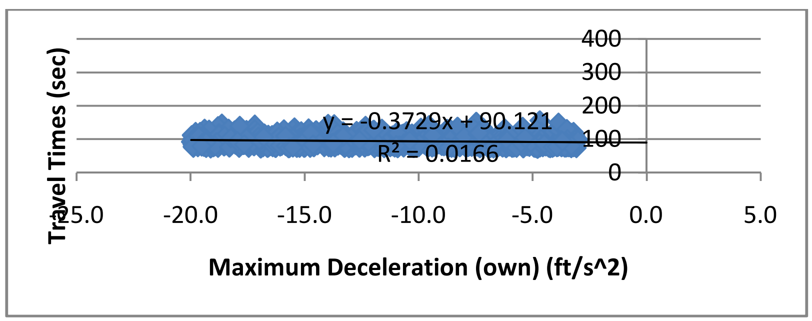
(b) Travel Time Segment #2



(c) Travel Time Segment #3

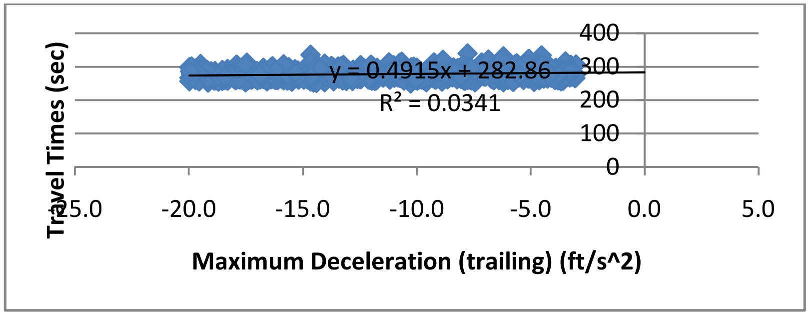


(d) Travel Time Segment #4

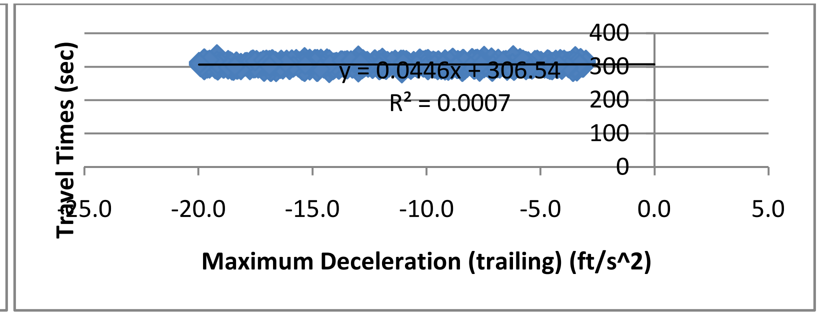


(e) Travel Time Segment #5

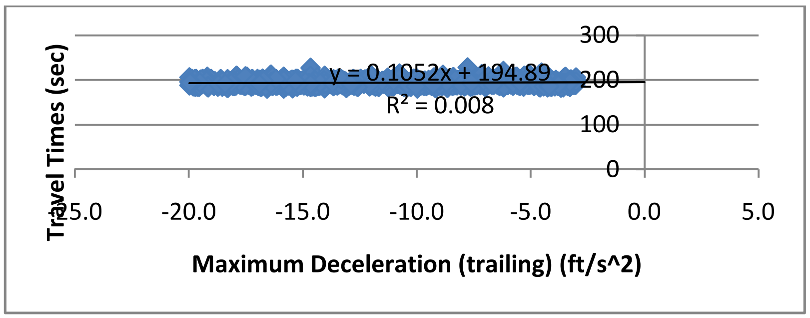
Figure 75(a-e): 75% Volume Scenario, Iteration #1, Parameter #8 Scatter Plots



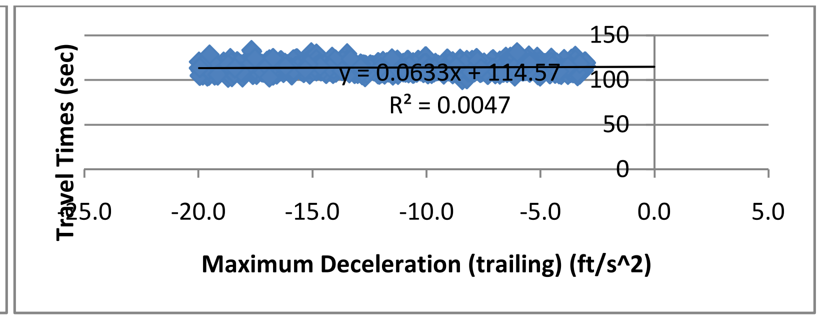
(a) Travel Time Segment #1



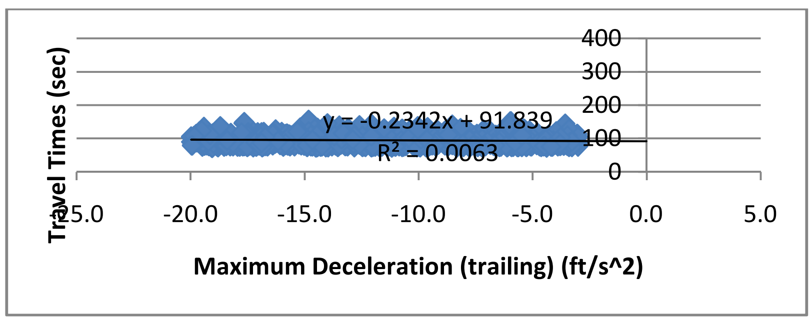
(b) Travel Time Segment #2



(c) Travel Time Segment #3

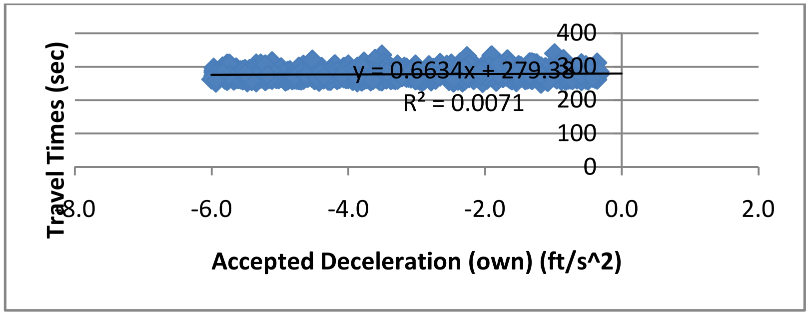


(d) Travel Time Segment #4

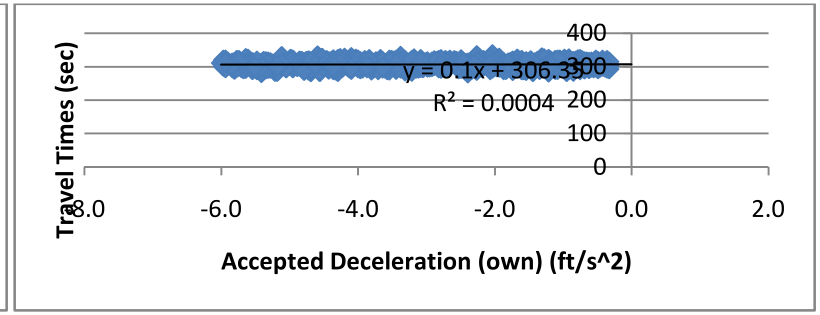


(e) Travel Time Segment #5

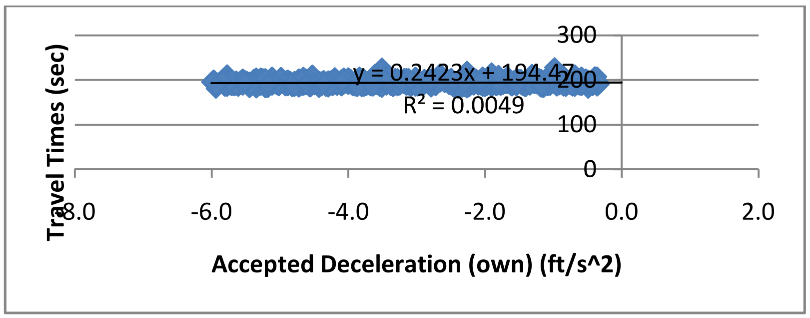
Figure 76(a-e): 75% Volume Scenario, Iteration #1, Parameter #9 Scatter Plots



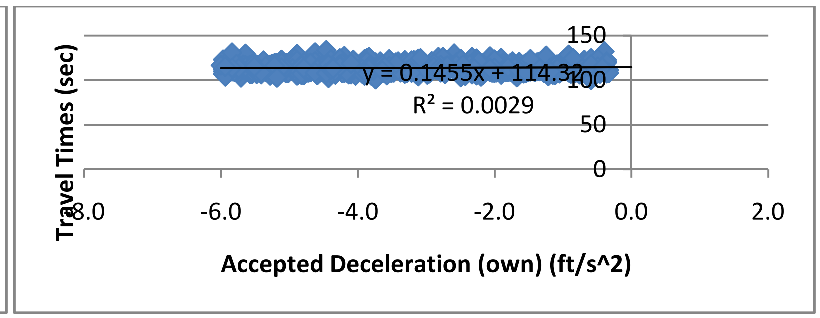
(a) Travel Time Segment #1



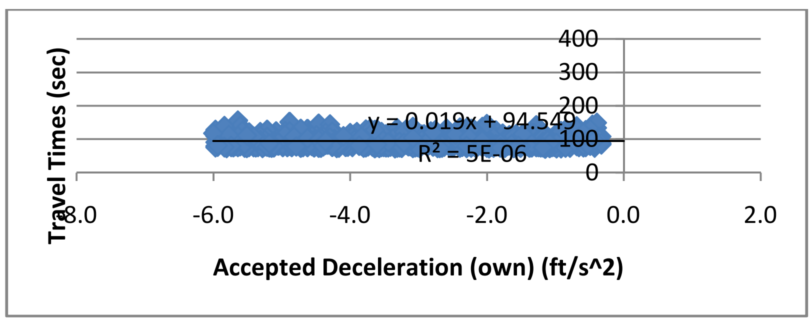
(b) Travel Time Segment #2



(c) Travel Time Segment #3

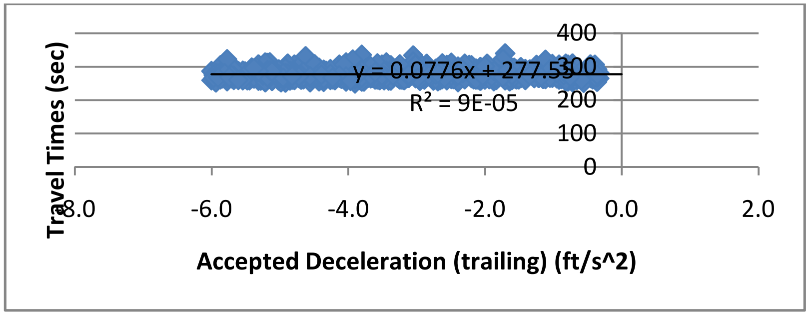


(d) Travel Time Segment #4

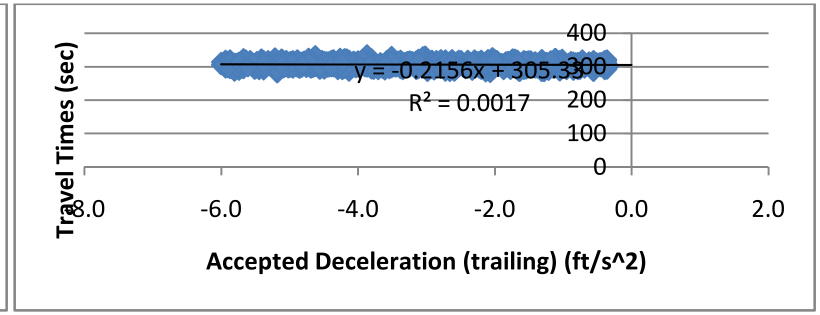


(e) Travel Time Segment #5

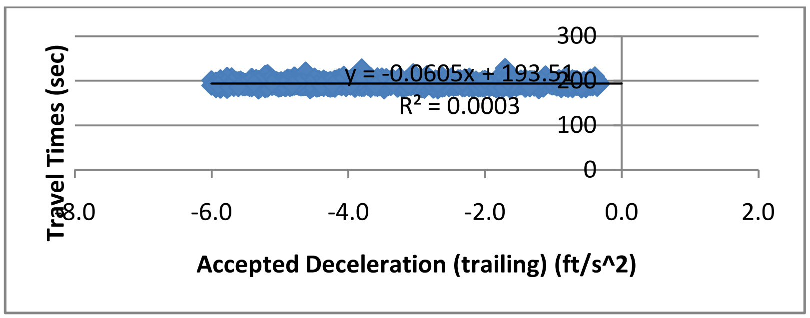
Figure 77(a-e): 75% Volume Scenario, Iteration #1, Parameter #10 Scatter Plots



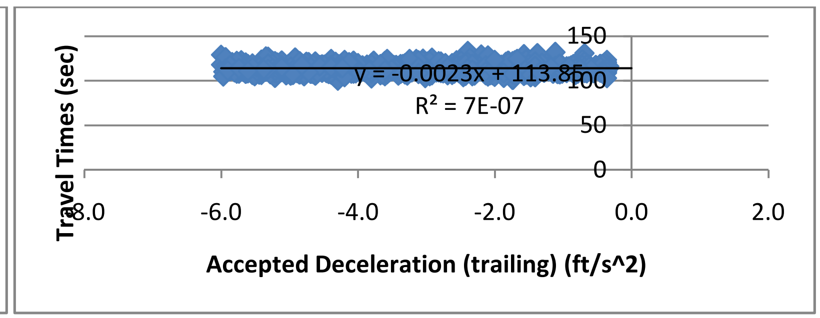
(a) Travel Time Segment #1



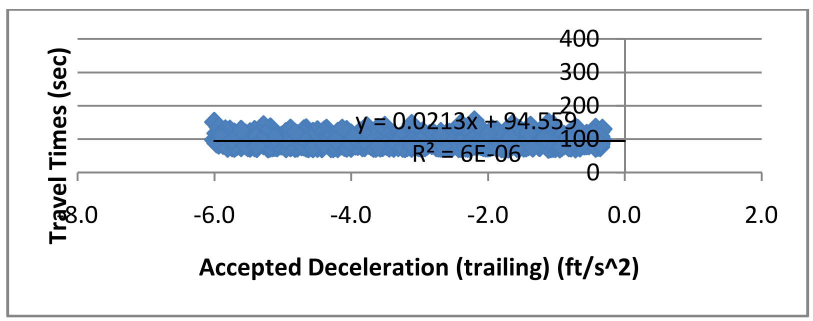
(b) Travel Time Segment #2



(c) Travel Time Segment #3

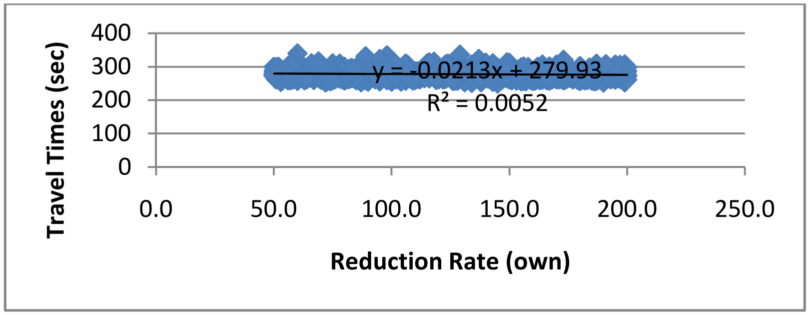


(d) Travel Time Segment #4

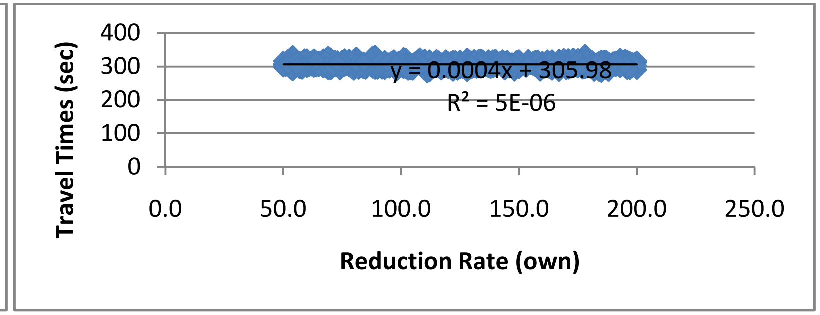


(e) Travel Time Segment #5

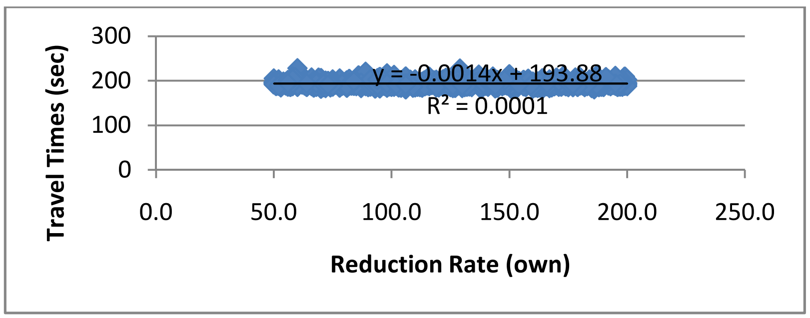
Figure 78(a-e): 75% Volume Scenario, Iteration #1, Parameter #11 Scatter Plots



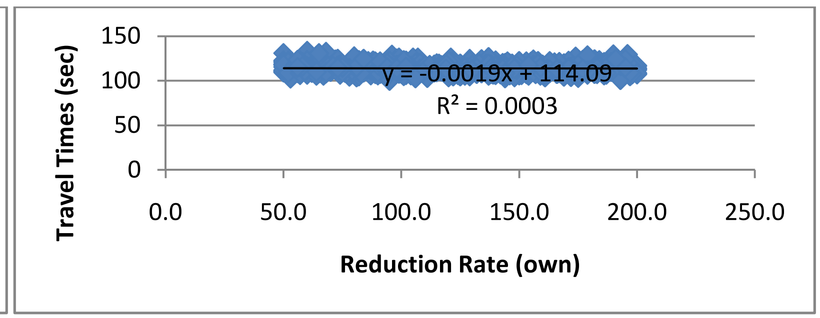
(a) Travel Time Segment #1



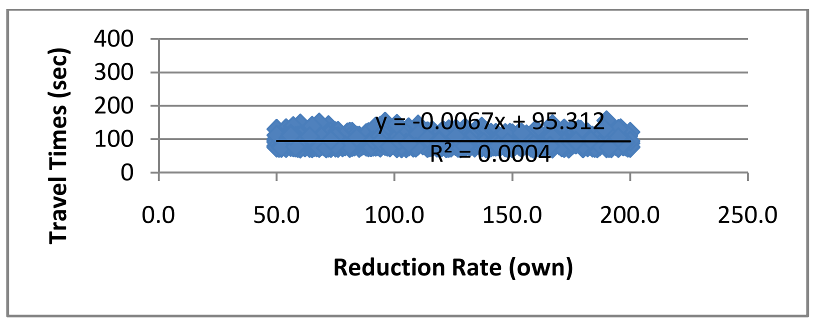
(b) Travel Time Segment #2



(c) Travel Time Segment #3

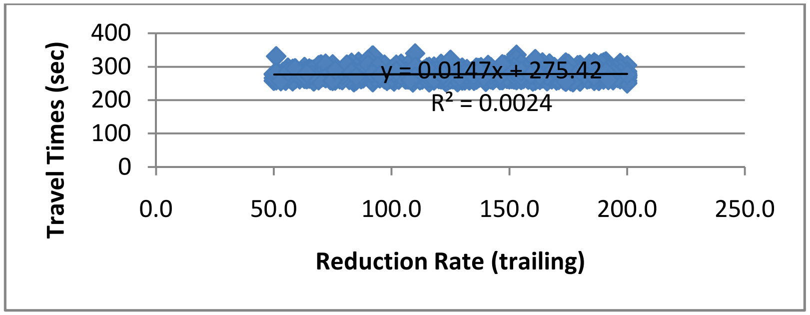


(d) Travel Time Segment #4

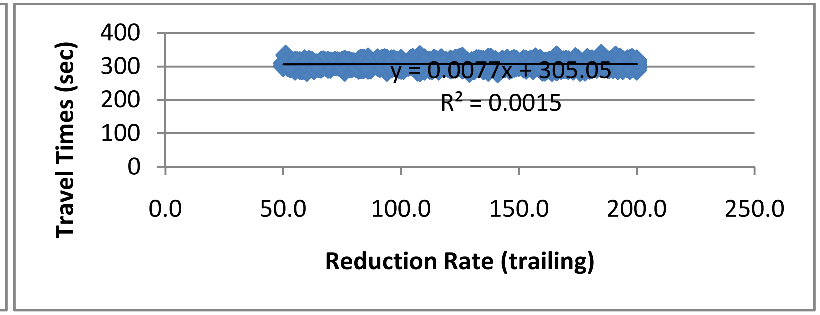


(e) Travel Time Segment #5

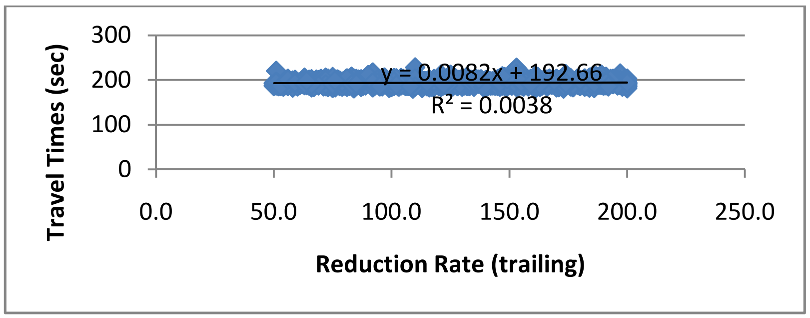
Figure 79(a-e): 75% Volume Scenario, Iteration #1, Parameter #12 Scatter Plots



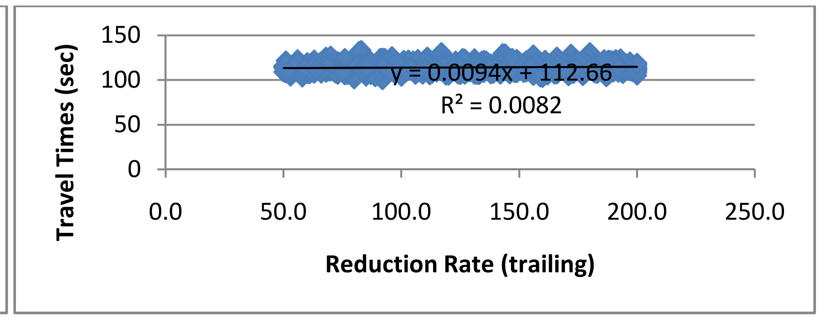
(a) Travel Time Segment #1



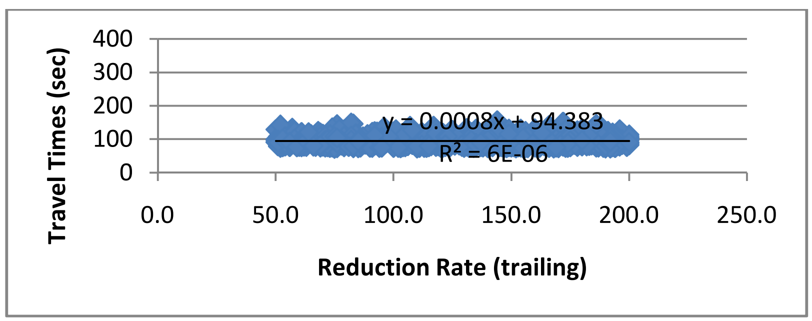
(b) Travel Time Segment #2



(c) Travel Time Segment #3

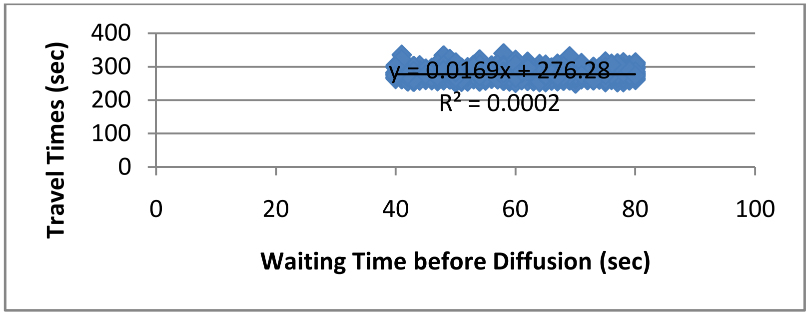


(d) Travel Time Segment #4

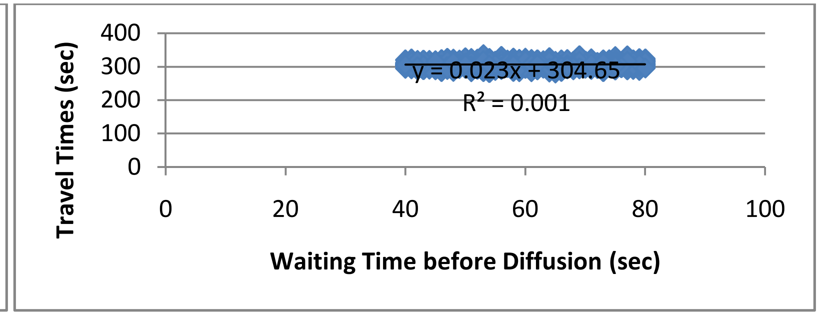


(e) Travel Time Segment #5

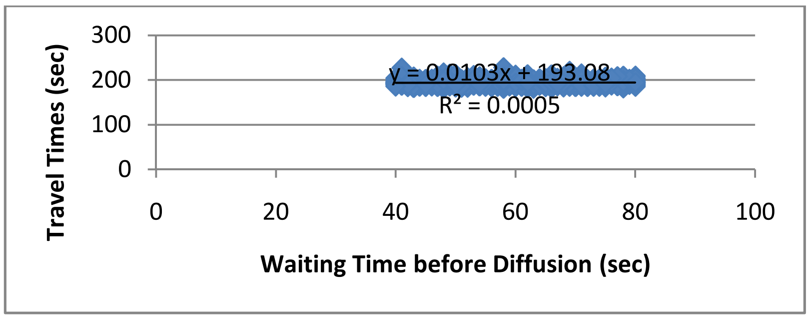
Figure 80(a-e): 75% Volume Scenario, Iteration #1, Parameter #13 Scatter Plots



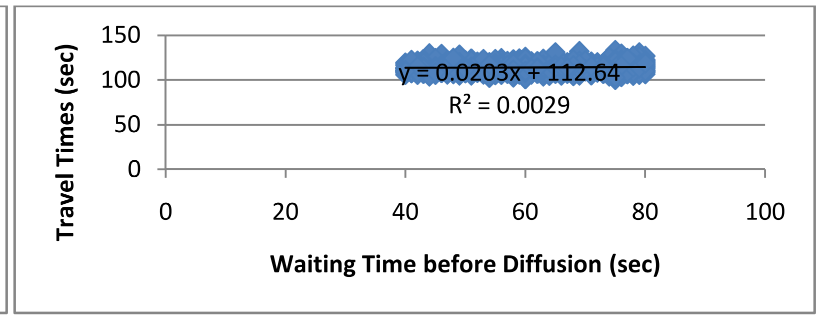
(a) Travel Time Segment #1



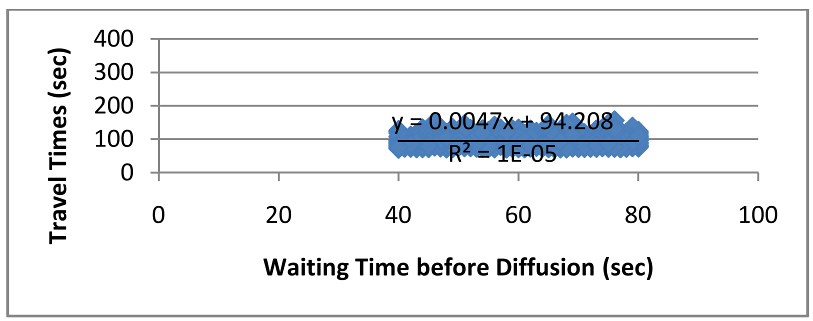
(b) Travel Time Segment #2



(c) Travel Time Segment #3

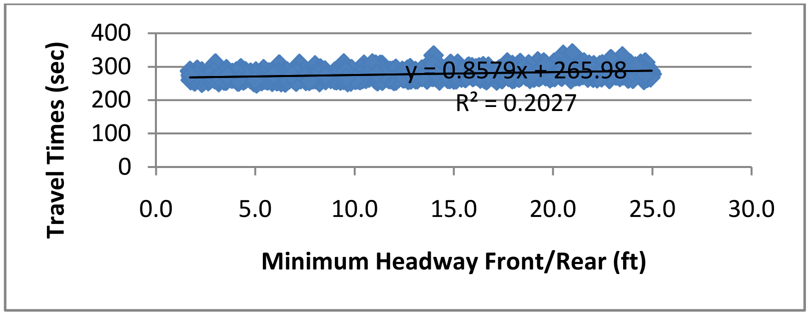


(d) Travel Time Segment #4

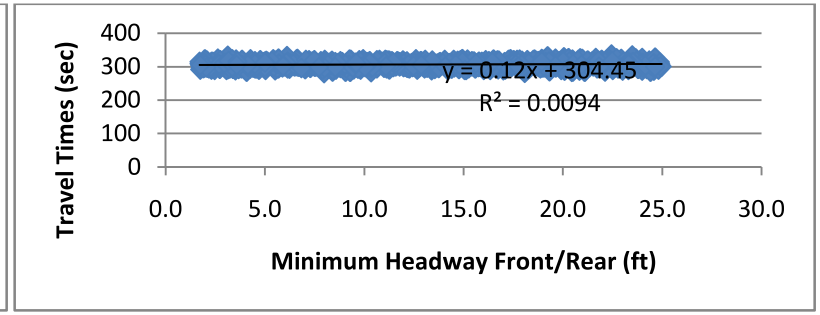


(e) Travel Time Segment #5

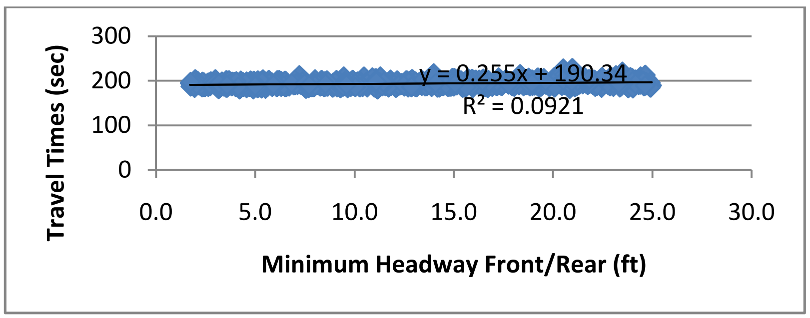
Figure 81(a-e): 75% Volume Scenario, Iteration #1, Parameter #14 Scatter Plots



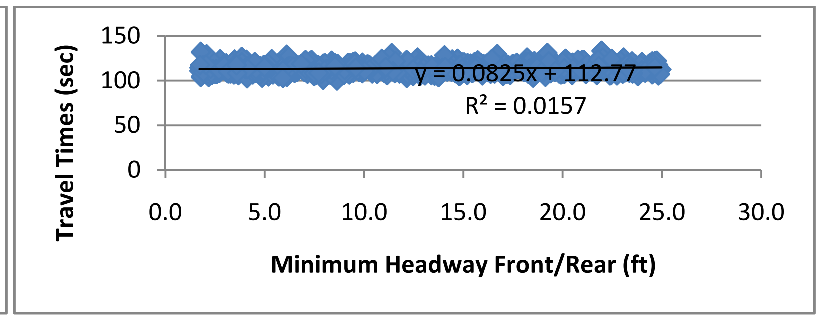
(a) Travel Time Segment #1



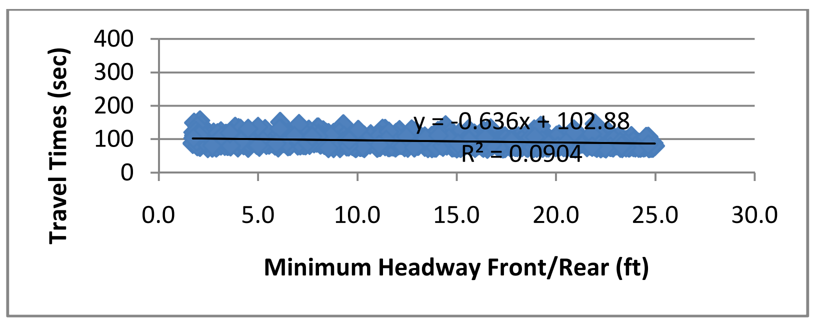
(b) Travel Time Segment #2



(c) Travel Time Segment #3

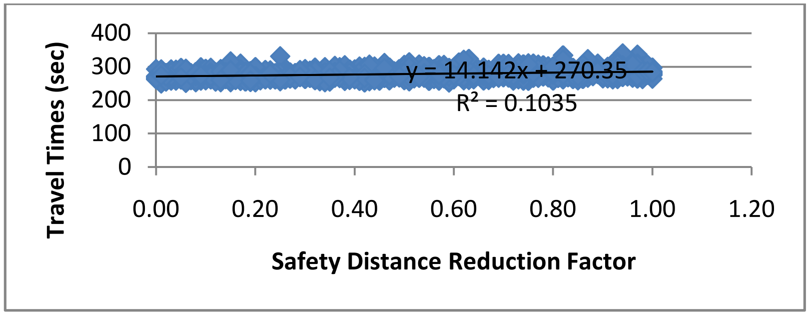


(d) Travel Time Segment #4

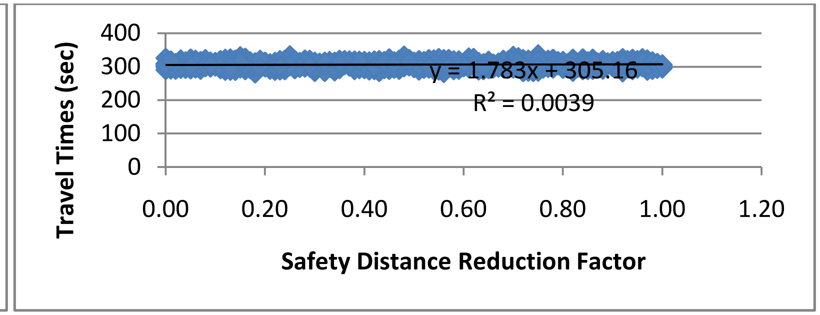


(e) Travel Time Segment #5

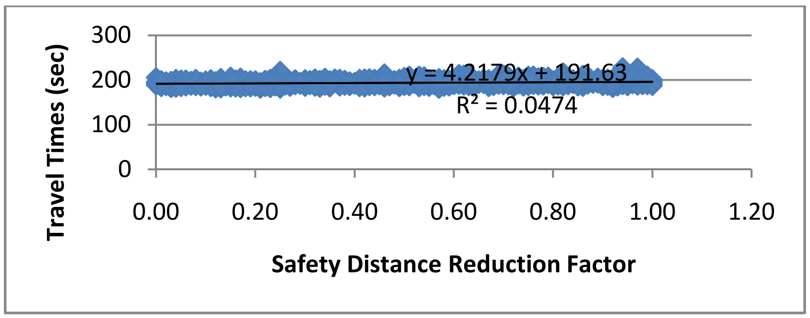
Figure 82(a-e): 75% Volume Scenario, Iteration #1, Parameter #15 Scatter Plots



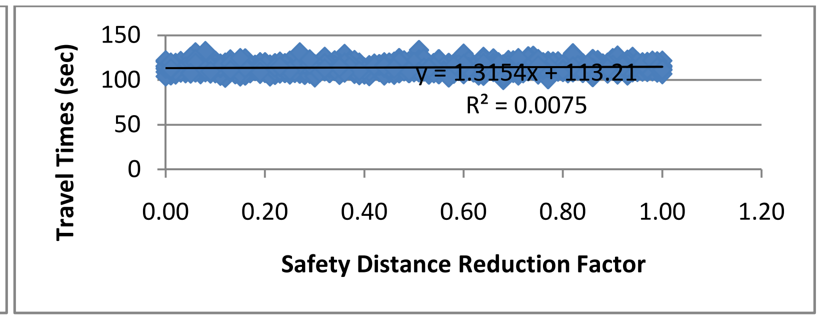
(a) Travel Time Segment #1



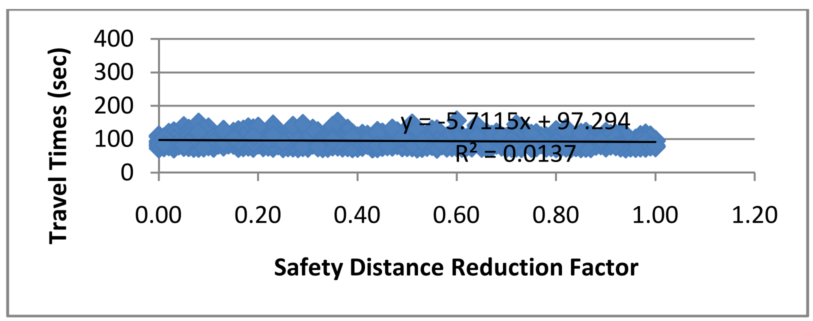
(b) Travel Time Segment #2



(c) Travel Time Segment #3

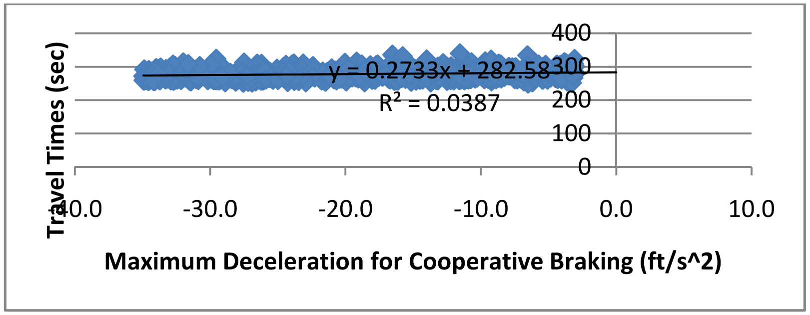


(d) Travel Time Segment #4

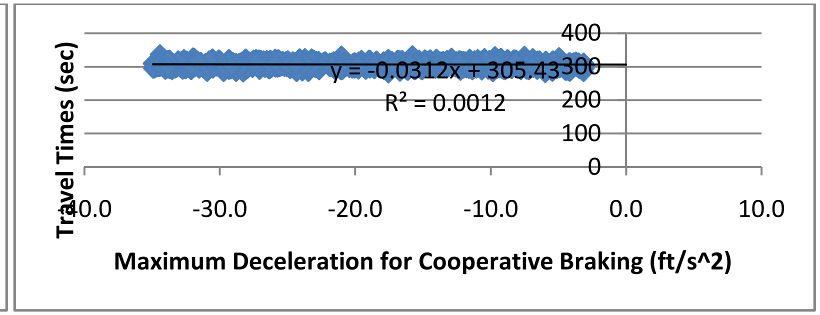


(e) Travel Time Segment #5

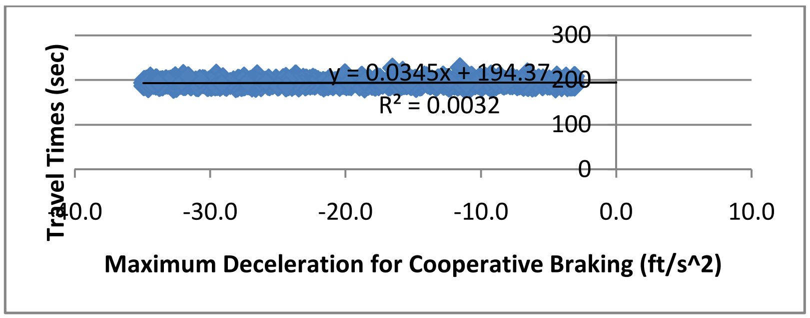
Figure 83(a-e): 75% Volume Scenario, Iteration #1, Parameter #16 Scatter Plots



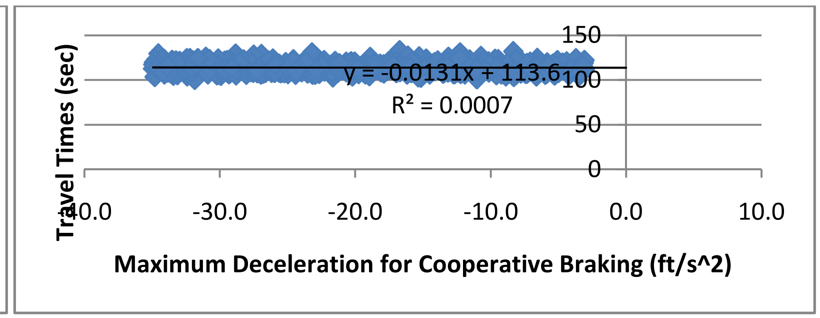
(a) Travel Time Segment #1



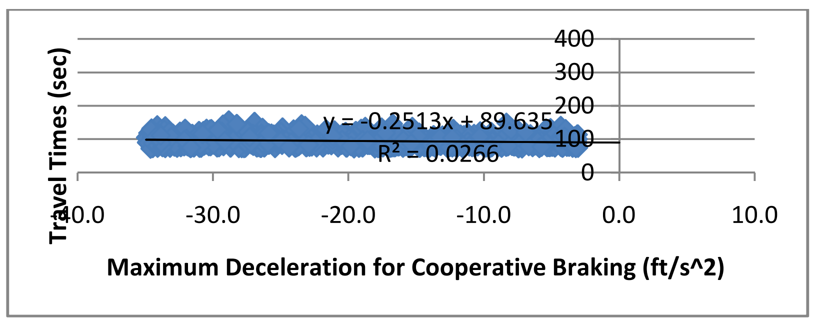
(b) Travel Time Segment #2



(c) Travel Time Segment #3

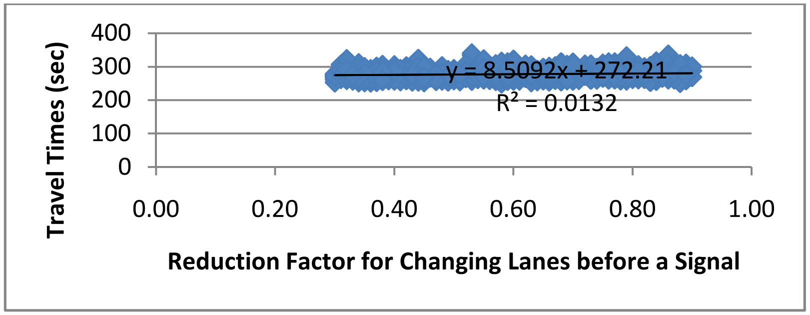


(d) Travel Time Segment #4

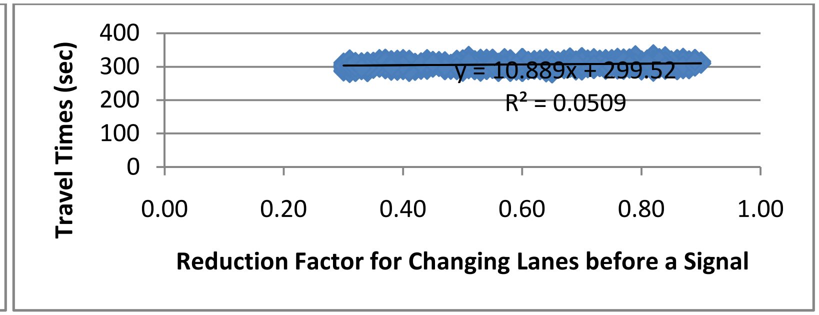


(e) Travel Time Segment #5

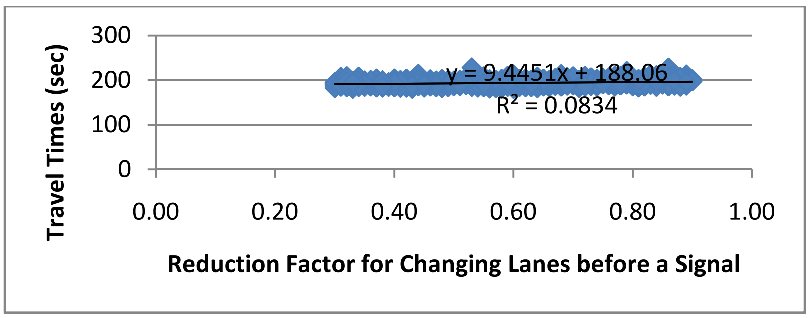
Figure 84(a-e): 75% Volume Scenario, Iteration #1, Parameter #17 Scatter Plots



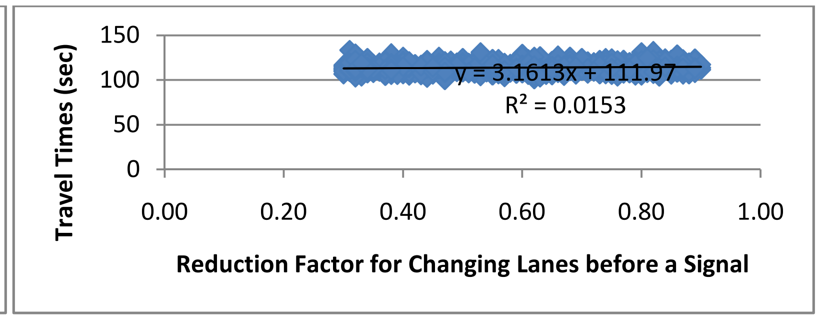
(a) Travel Time Segment #1



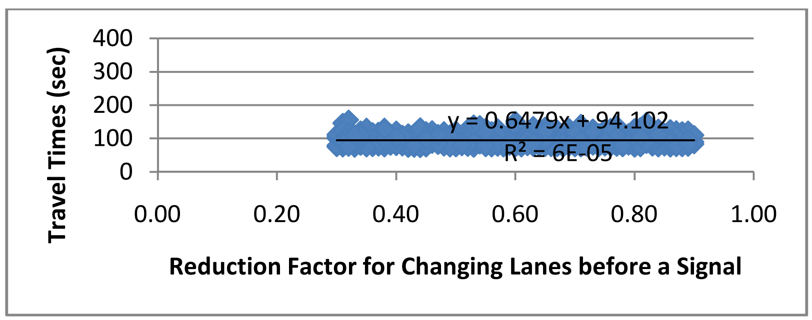
(b) Travel Time Segment #2



(c) Travel Time Segment #3

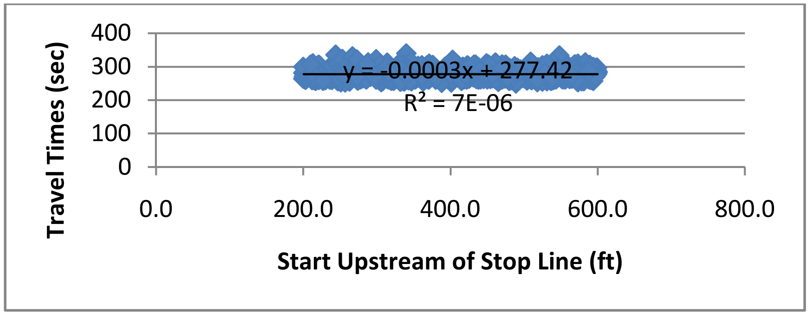


(d) Travel Time Segment #4

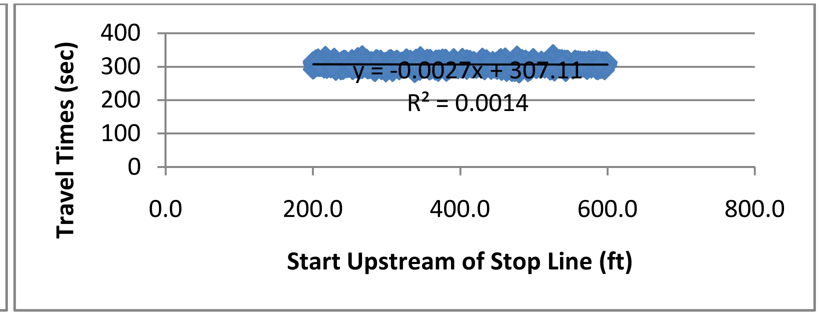


(e) Travel Time Segment #5

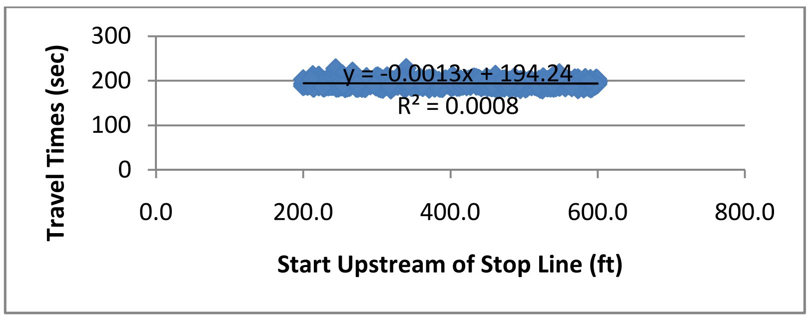
Figure 85(a-e): 75% Volume Scenario, Iteration #1, Parameter #18 Scatter Plots



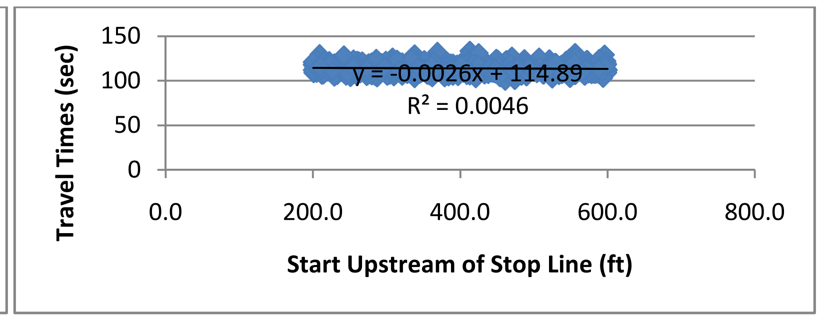
(a) Travel Time Segment #1



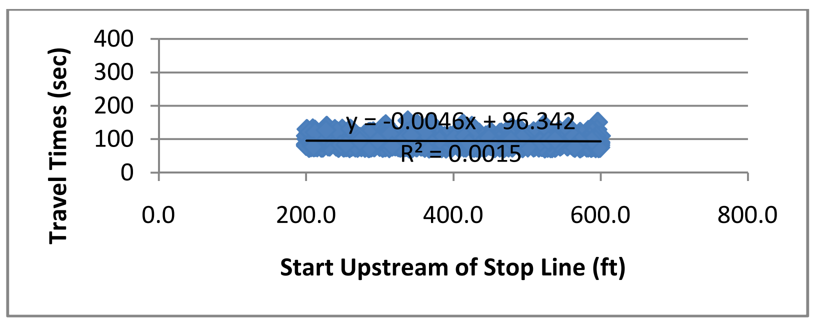
(b) Travel Time Segment #2



(c) Travel Time Segment #3

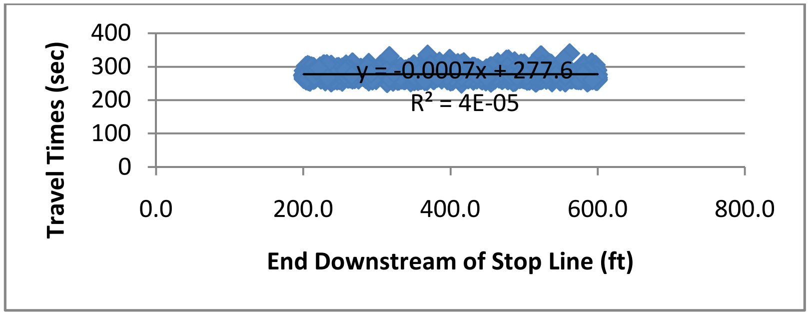


(d) Travel Time Segment #4

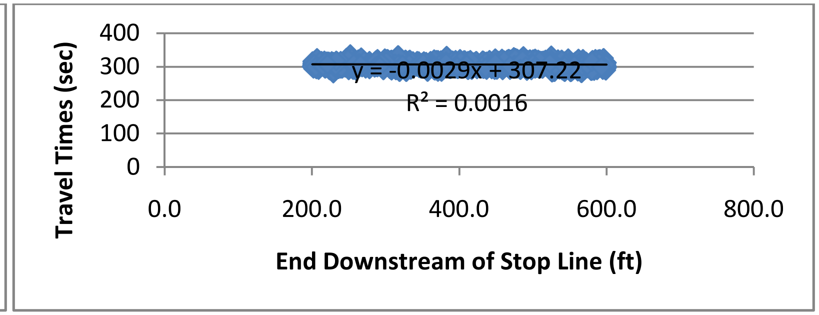


(e) Travel Time Segment #5

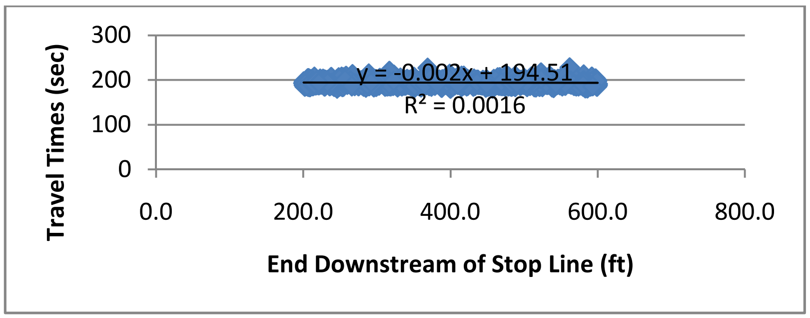
Figure 86(a-e): 75% Volume Scenario, Iteration #1, Parameter #19 Scatter Plots



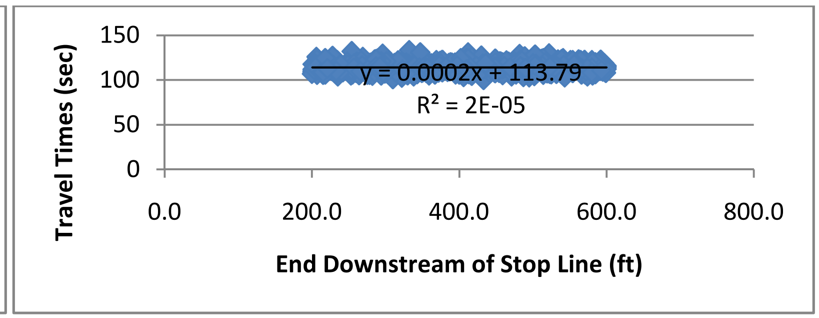
(a) Travel Time Segment #1



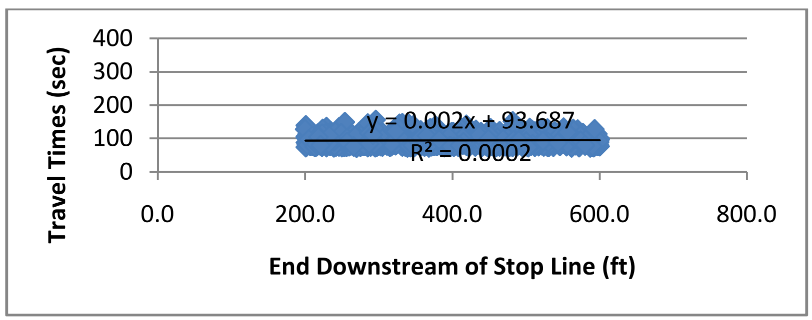
(b) Travel Time Segment #2



(c) Travel Time Segment #3

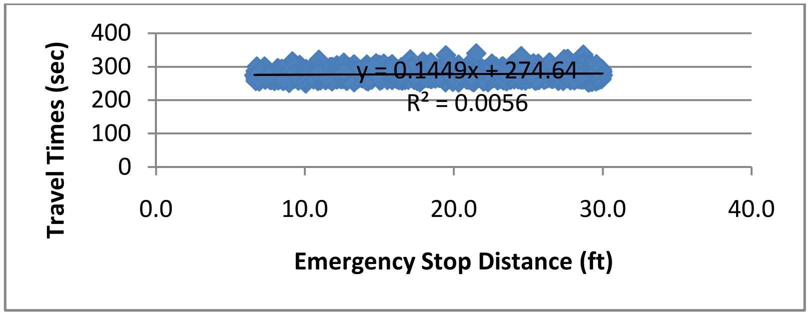


(d) Travel Time Segment #4

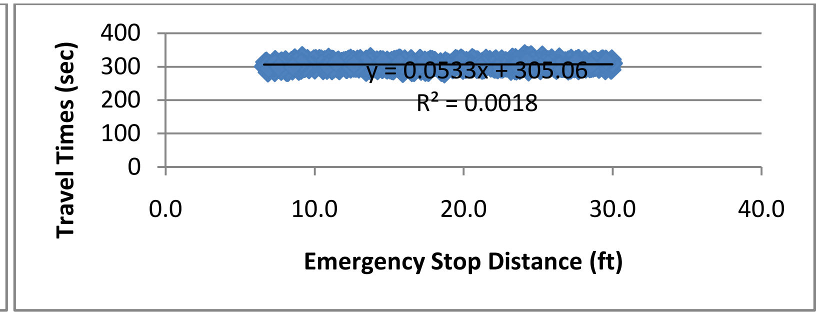


(e) Travel Time Segment #5

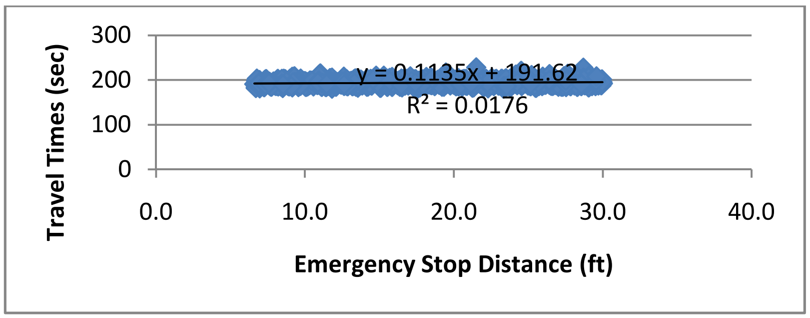
Figure 87(a-e): 75% Volume Scenario, Iteration #1, Parameter #20 Scatter Plots



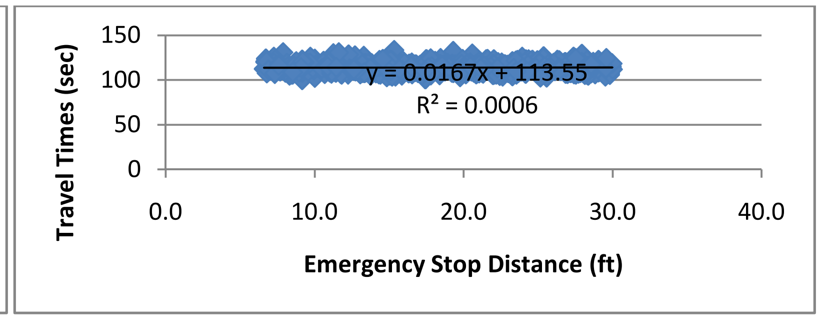
(a) Travel Time Segment #1



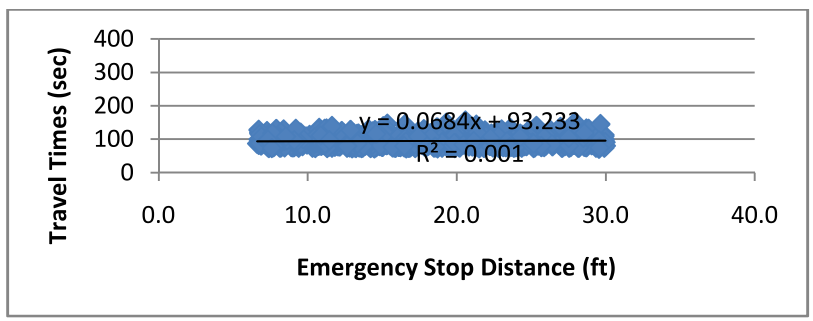
(b) Travel Time Segment #2



(c) Travel Time Segment #3

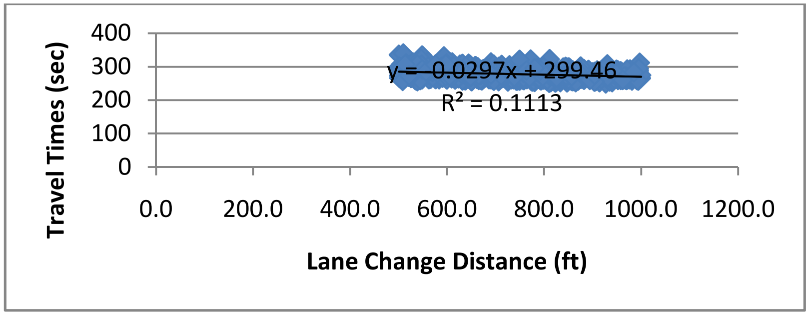


(d) Travel Time Segment #4

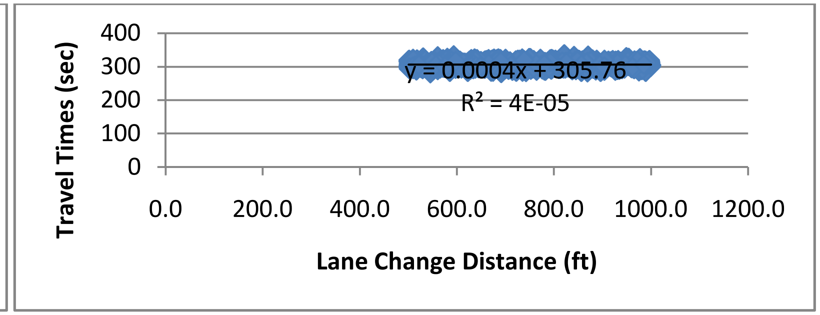


(e) Travel Time Segment #5

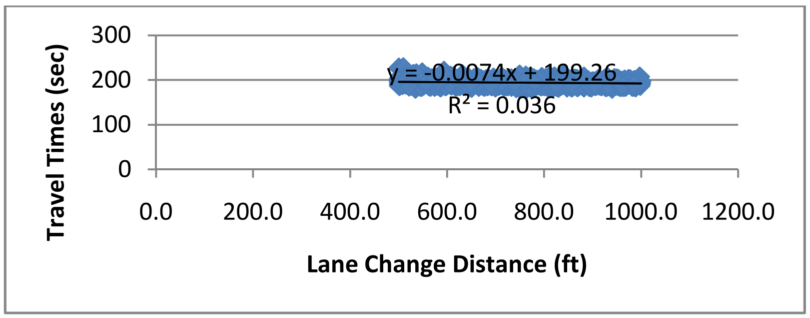
Figure 88(a-e): 75% Volume Scenario, Iteration #1, Parameter #21 Scatter Plots



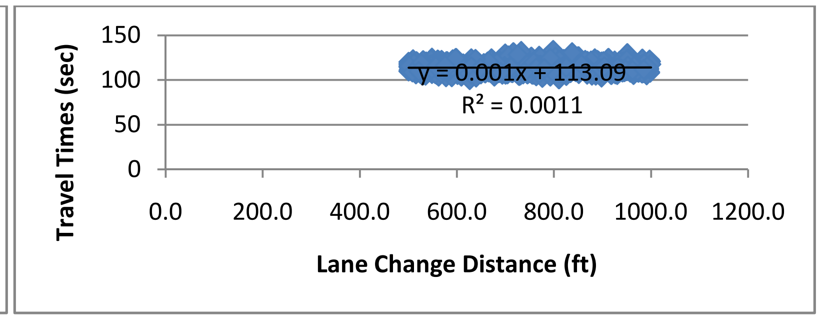
(a) Travel Time Segment #1



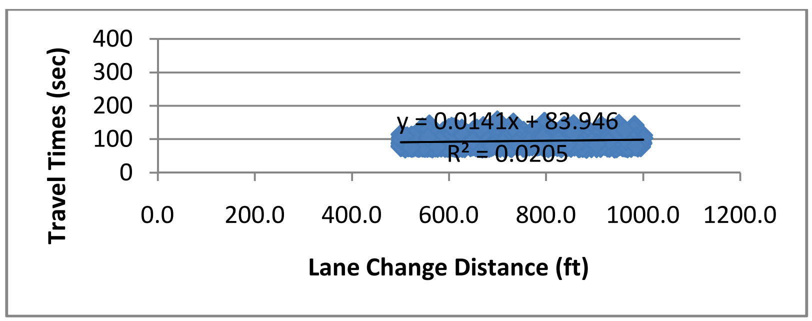
(b) Travel Time Segment #2



(c) Travel Time Segment #3

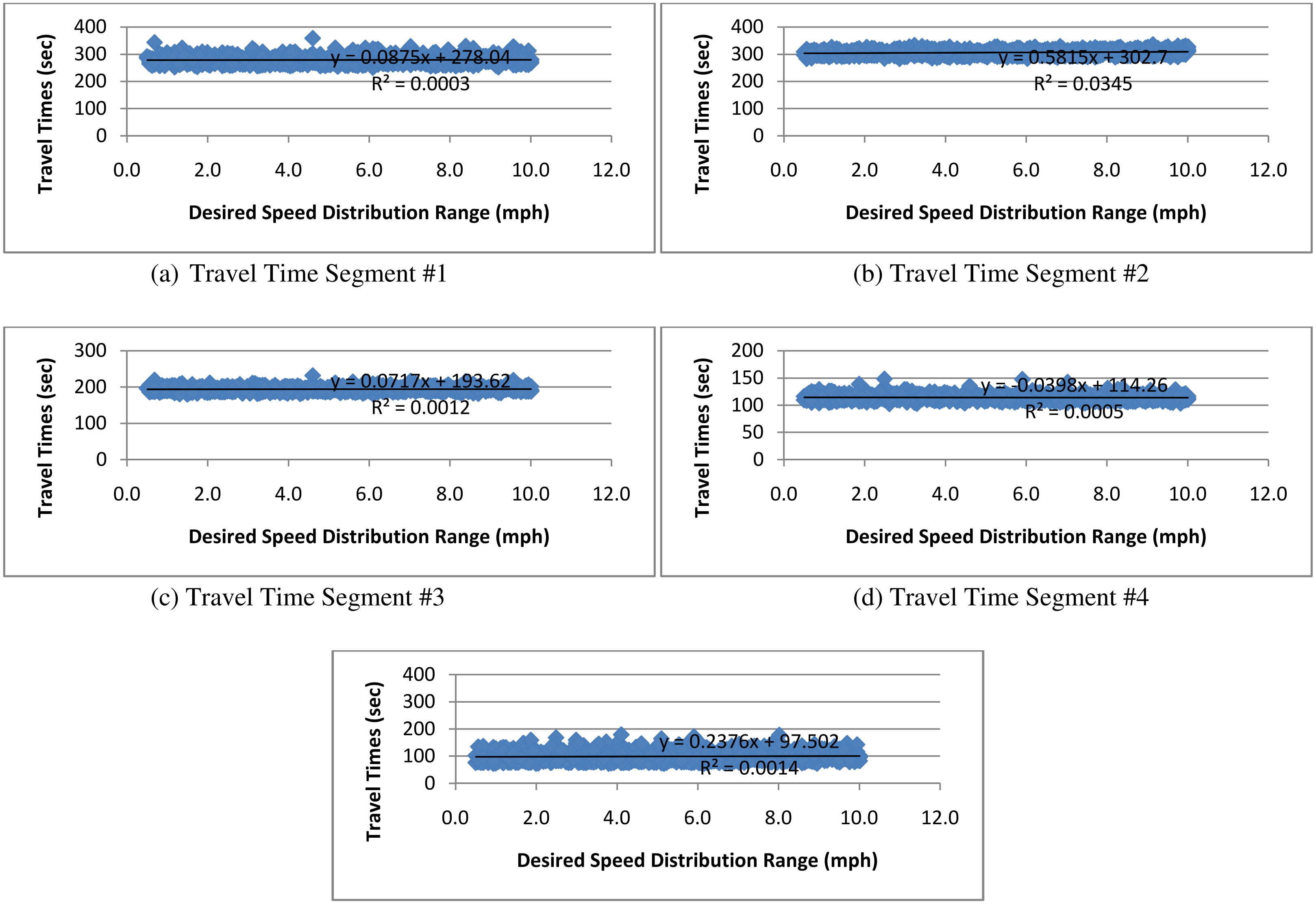


(d) Travel Time Segment #4



(e) Travel Time Segment #5

Figure 89(a-e): 75% Volume Scenario, Iteration #1, Parameter #22 Scatter Plots



(a) Travel Time Segment #1

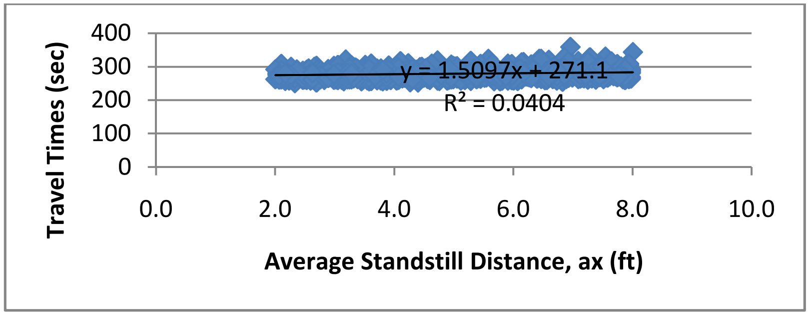
(b) Travel Time Segment #2

(c) Travel Time Segment #3

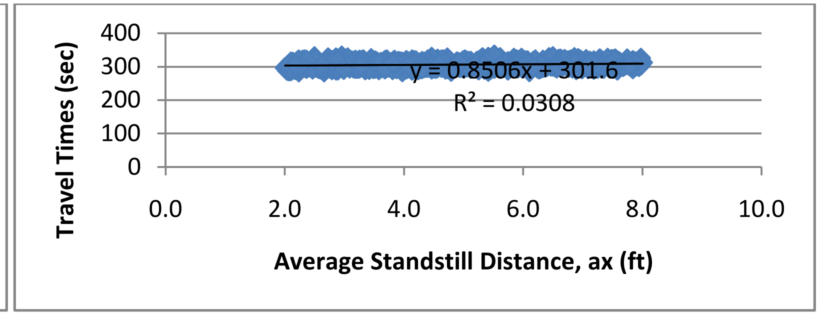
(d) Travel Time Segment #4

(e) Travel Time Segment #5

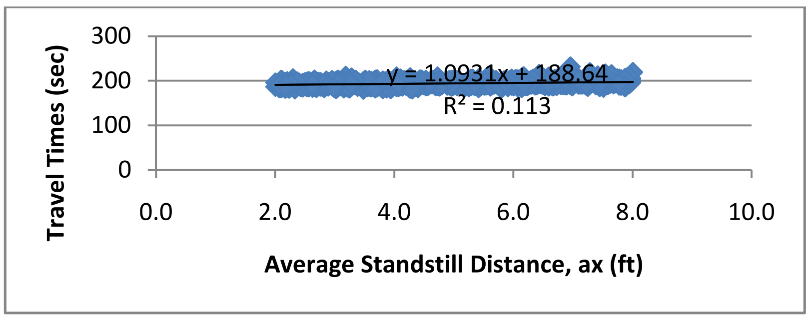
Figure 90(a-e): 75% Volume Scenario, Iteration #2, Parameter #1 Scatter Plots



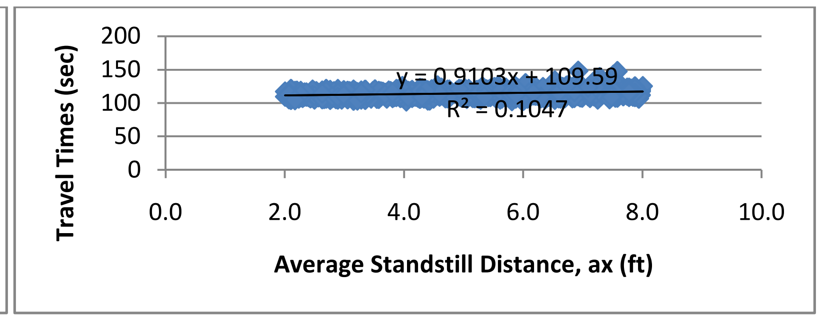
(a) Travel Time Segment #1



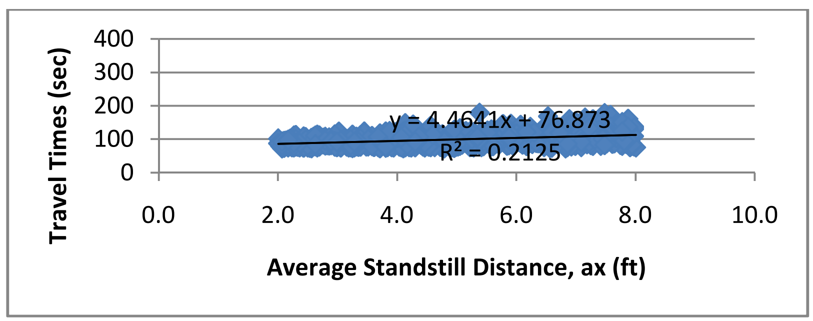
(b) Travel Time Segment #2



(c) Travel Time Segment #3

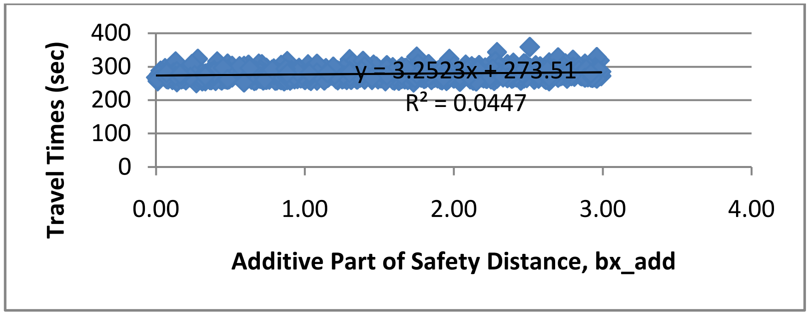


(d) Travel Time Segment #4

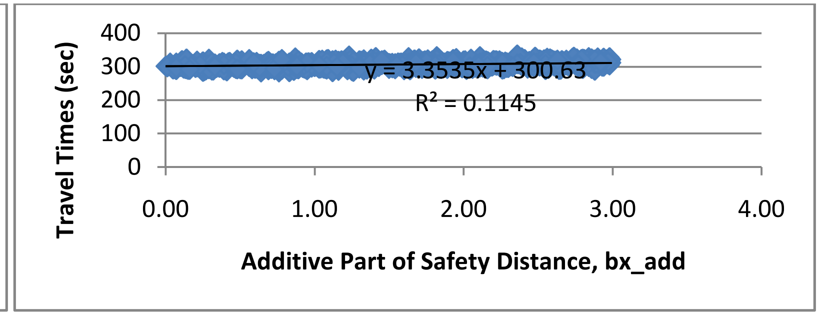


(e) Travel Time Segment #5

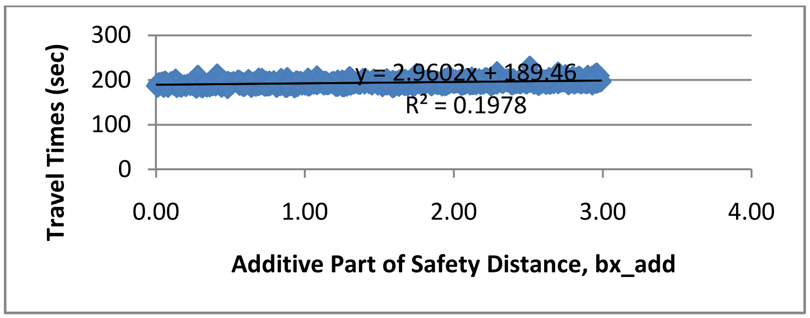
Figure 91(a-e): 75% Volume Scenario, Iteration #2, Parameter #5 Scatter Plots



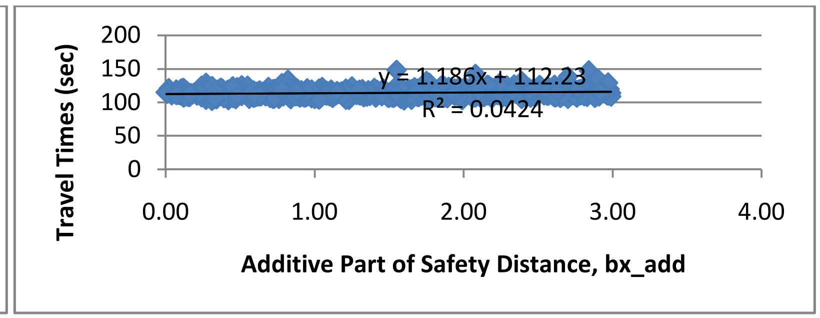
(a) Travel Time Segment #1



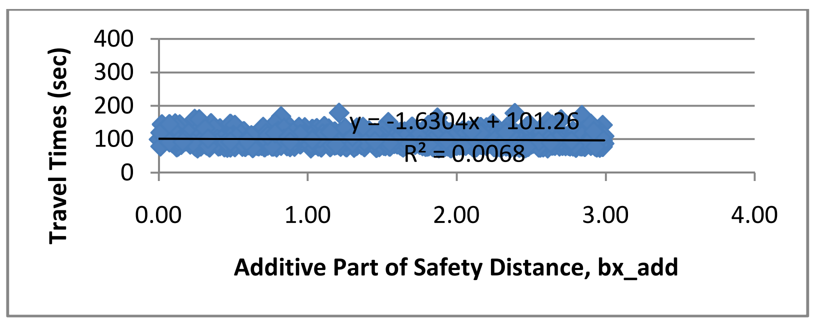
(b) Travel Time Segment #2



(c) Travel Time Segment #3

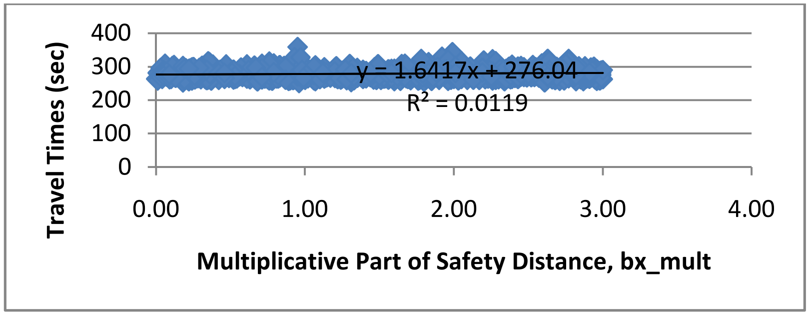


(d) Travel Time Segment #4

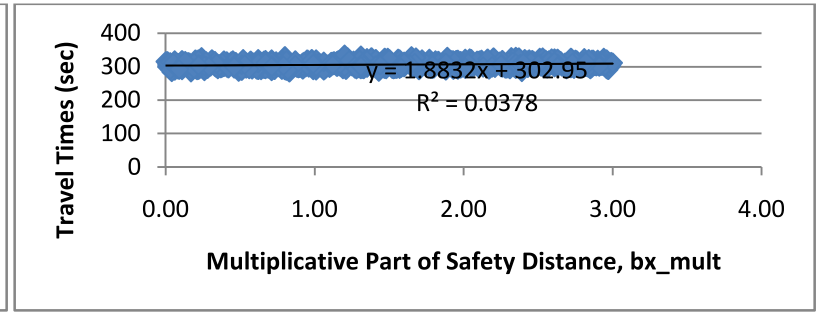


(e) Travel Time Segment #5

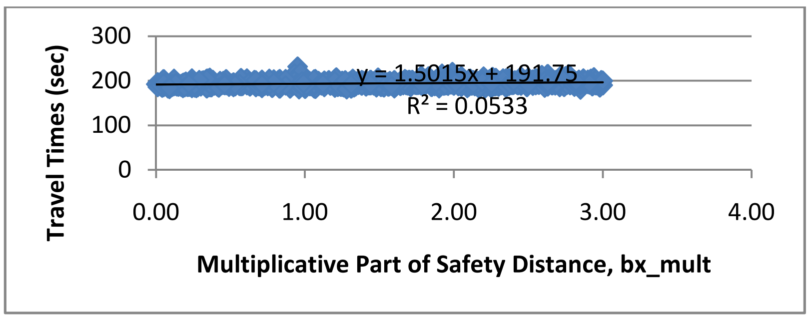
Figure 92(a-e): 75% Volume Scenario, Iteration #2, Parameter #6 Scatter Plots



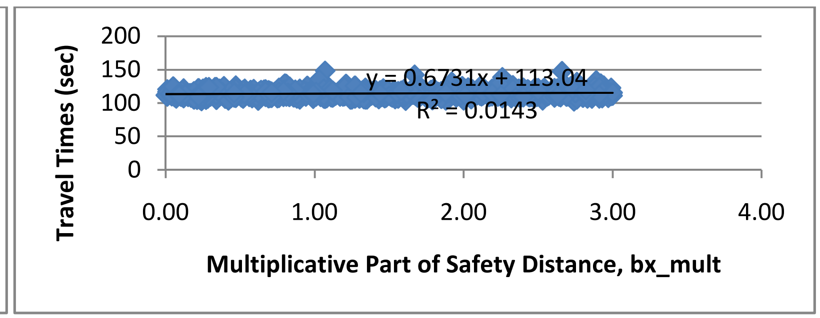
(a) Travel Time Segment #1



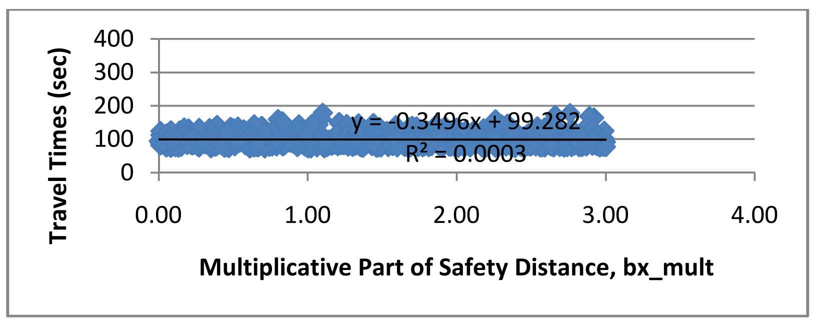
(b) Travel Time Segment #2



(c) Travel Time Segment #3

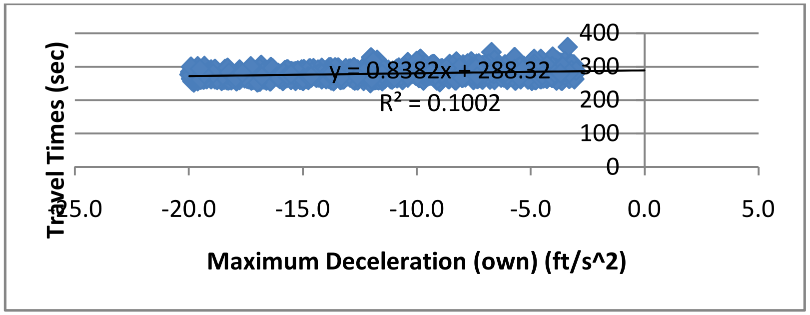


(d) Travel Time Segment #4

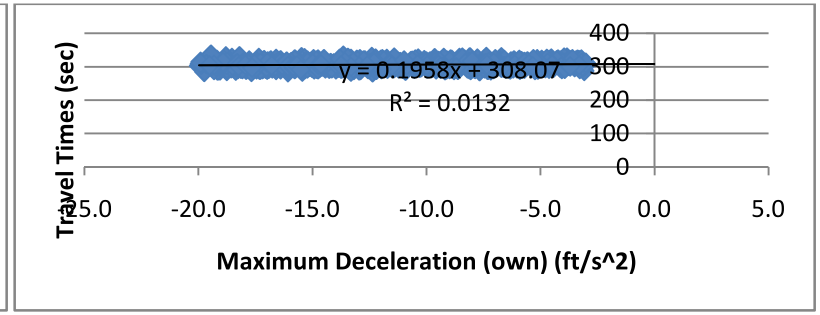


(e) Travel Time Segment #5

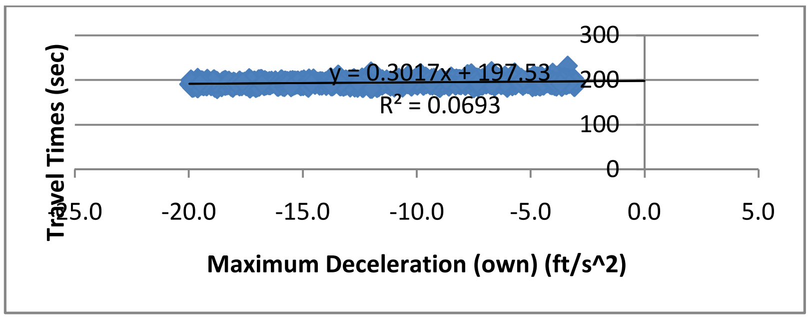
Figure 93(a-e): 75% Volume Scenario, Iteration #2, Parameter #7 Scatter Plots



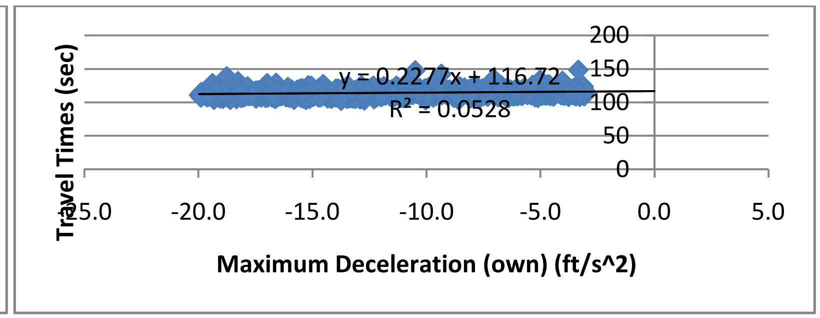
(a) Travel Time Segment #1



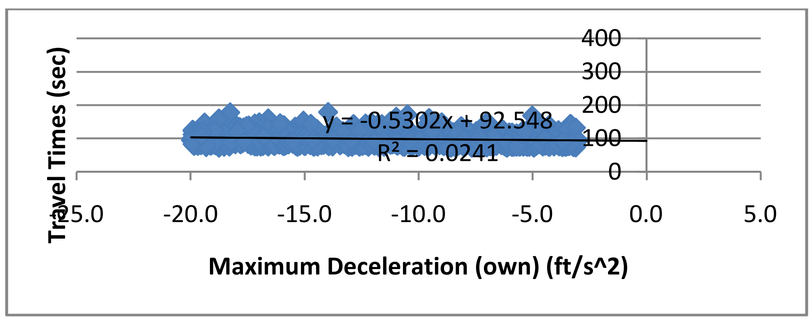
(b) Travel Time Segment #2



(c) Travel Time Segment #3

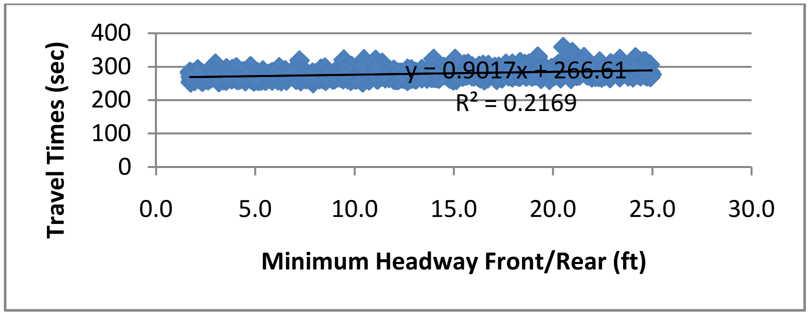


(d) Travel Time Segment #4

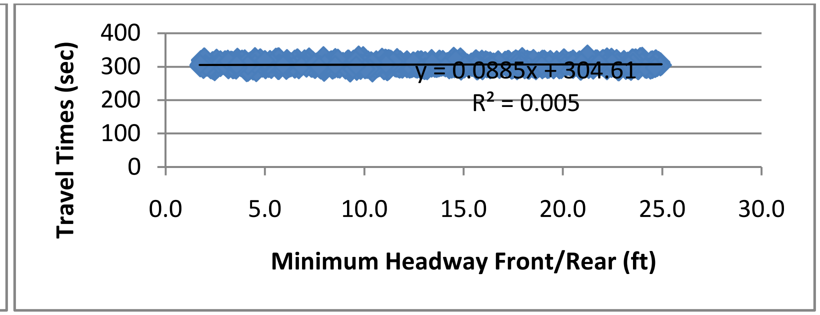


(e) Travel Time Segment #5

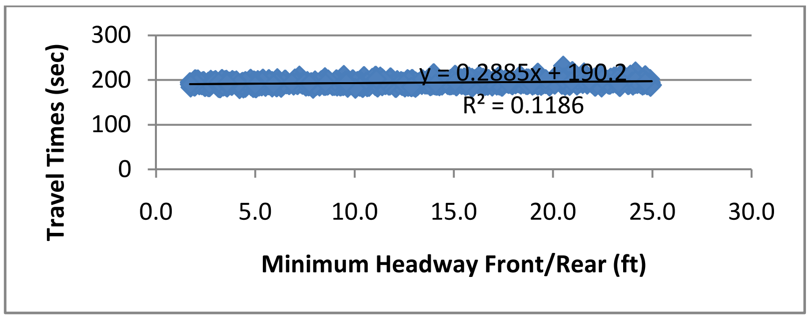
Figure 94(a-e): 75% Volume Scenario, Iteration #2, Parameter #8 Scatter Plots



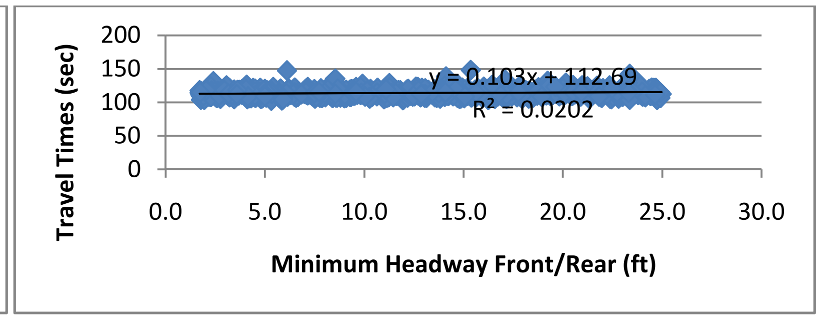
(a) Travel Time Segment #1



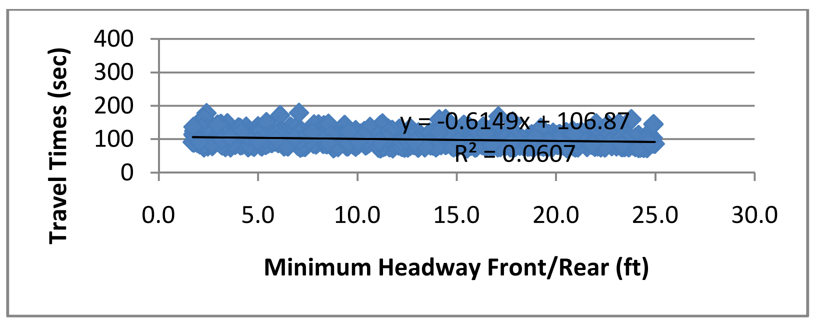
(b) Travel Time Segment #2



(c) Travel Time Segment #3

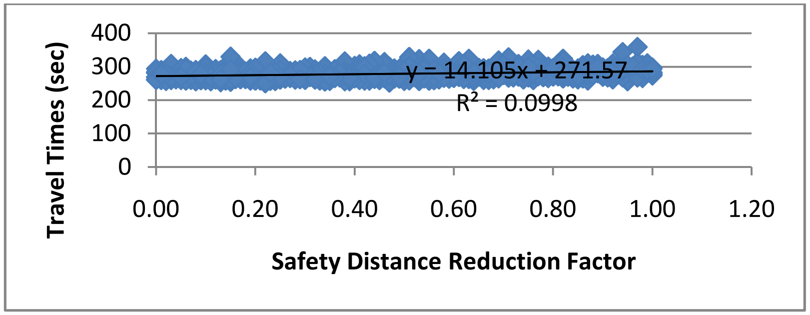


(d) Travel Time Segment #4

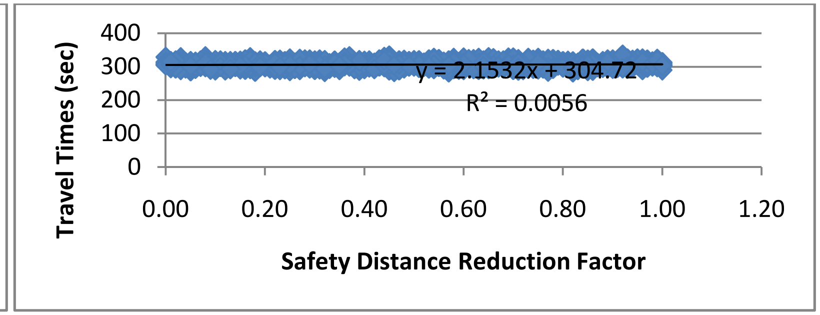


(e) Travel Time Segment #5

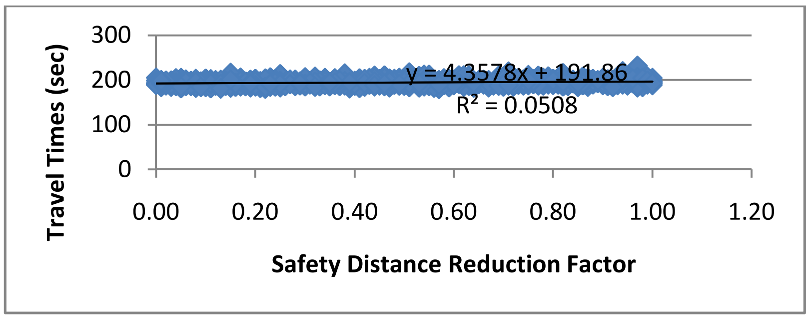
Figure 95(a-e): 75% Volume Scenario, Iteration #2, Parameter #15 Scatter Plots



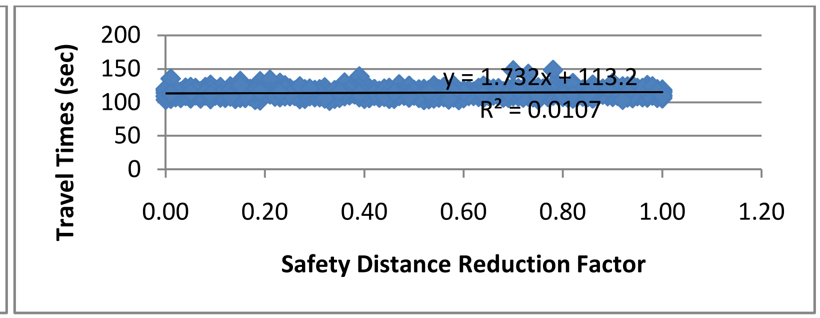
(a) Travel Time Segment #1



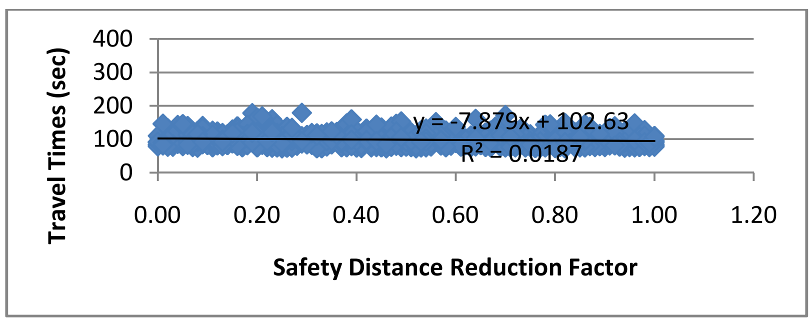
(b) Travel Time Segment #2



(c) Travel Time Segment #3

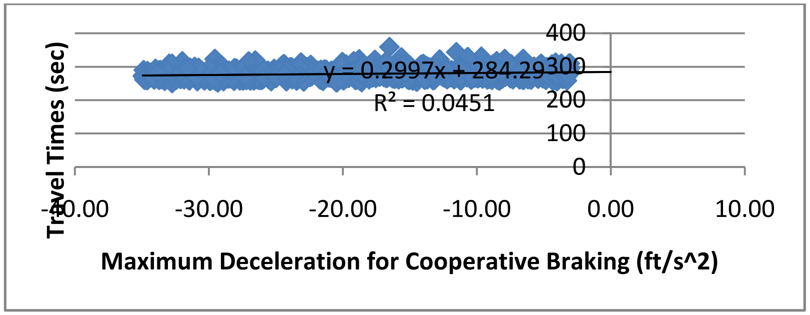


(d) Travel Time Segment #4

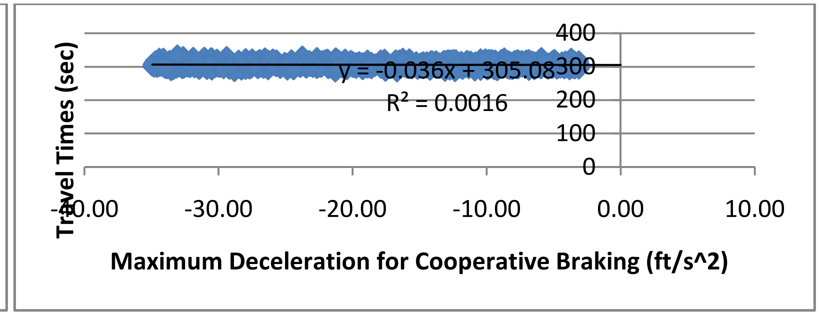


(e) Travel Time Segment #5

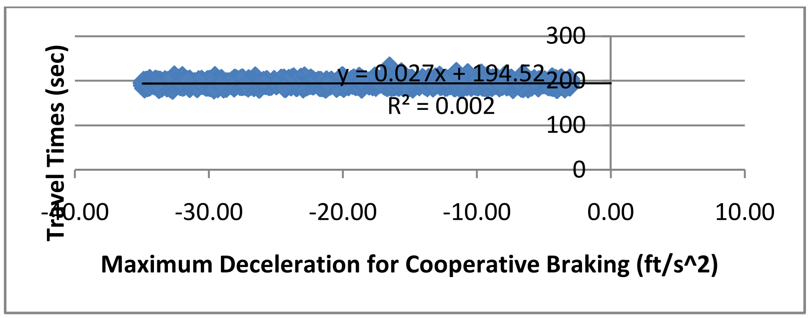
Figure 96(a-e): 75% Volume Scenario, Iteration #2, Parameter #16 Scatter Plots



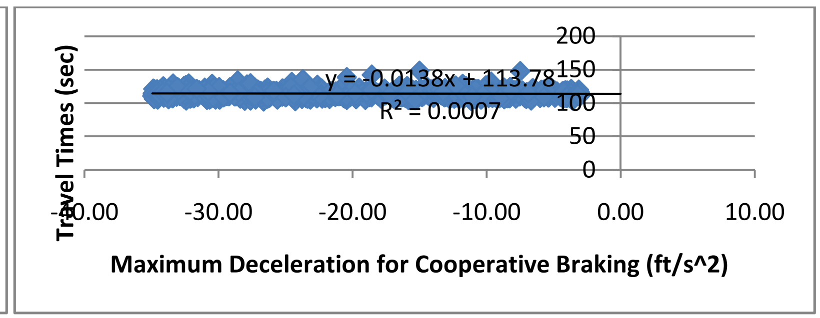
(a) Travel Time Segment #1



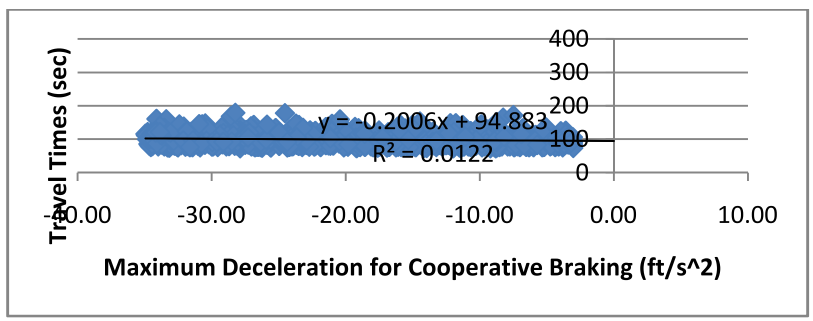
(b) Travel Time Segment #2



(c) Travel Time Segment #3

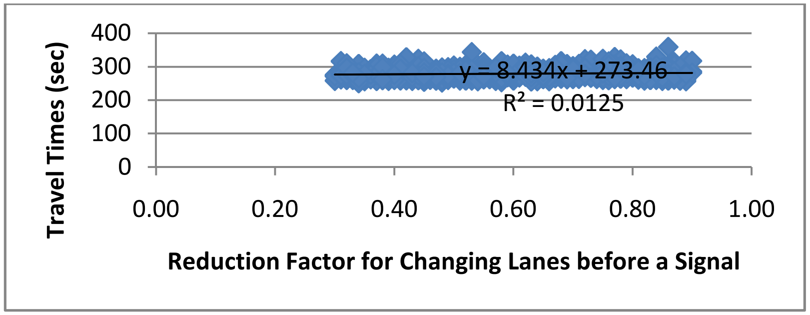


(d) Travel Time Segment #4

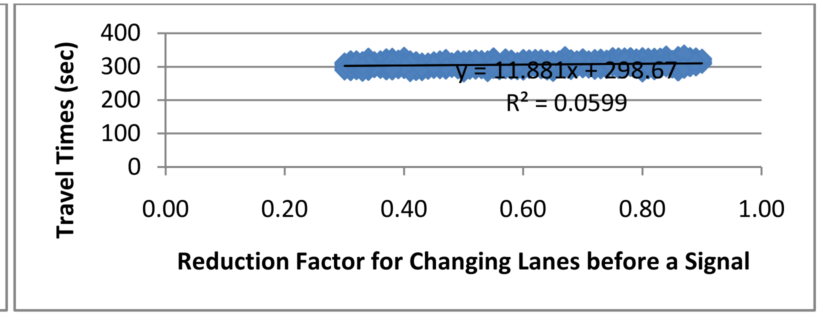


(e) Travel Time Segment #5

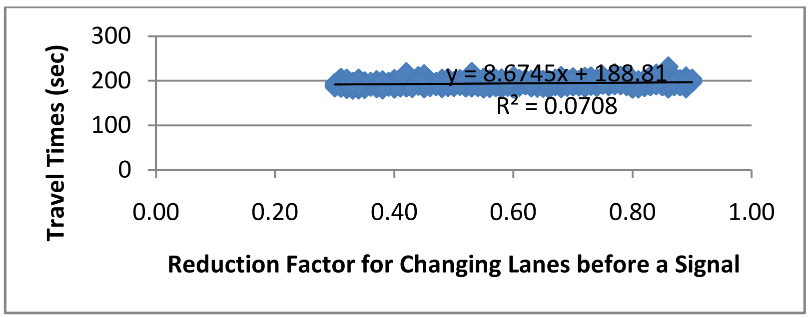
Figure 97(a-e): 75% Volume Scenario, Iteration #2, Parameter #17 Scatter Plots



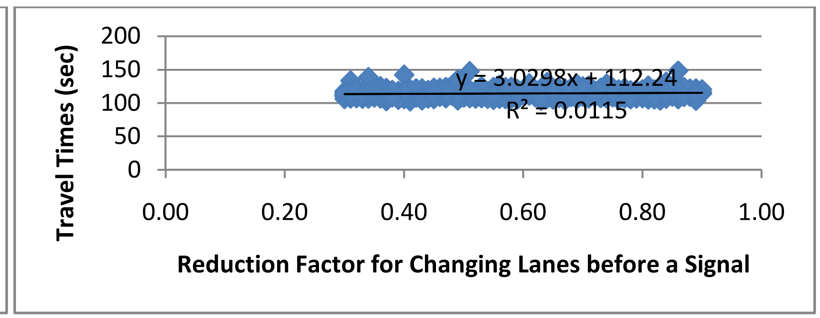
(a) Travel Time Segment #1



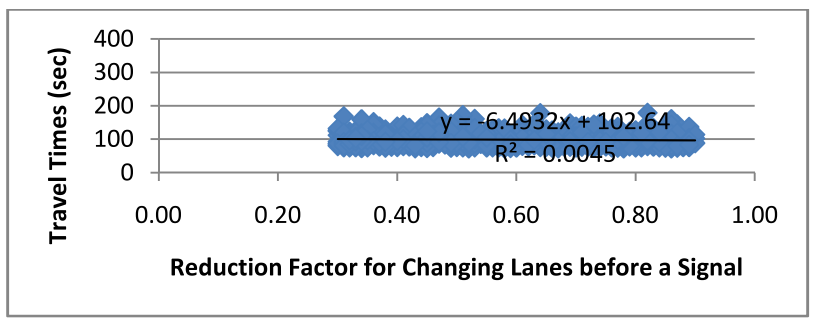
(b) Travel Time Segment #2



(c) Travel Time Segment #3

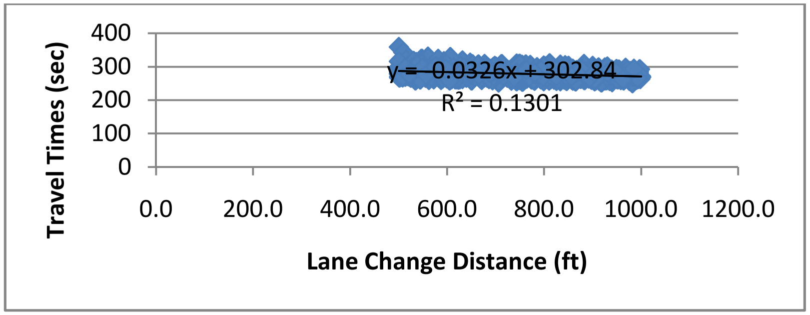


(d) Travel Time Segment #4

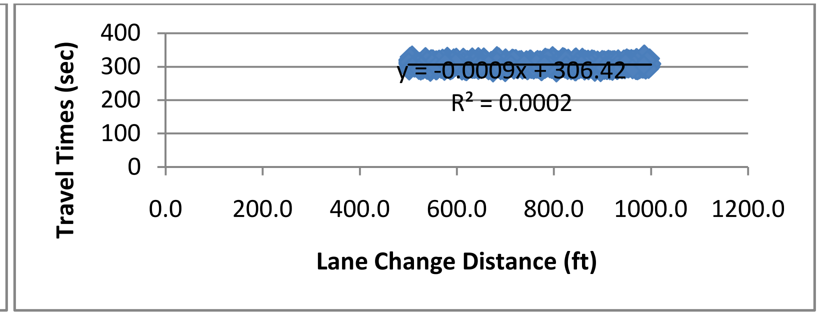


(e) Travel Time Segment #5

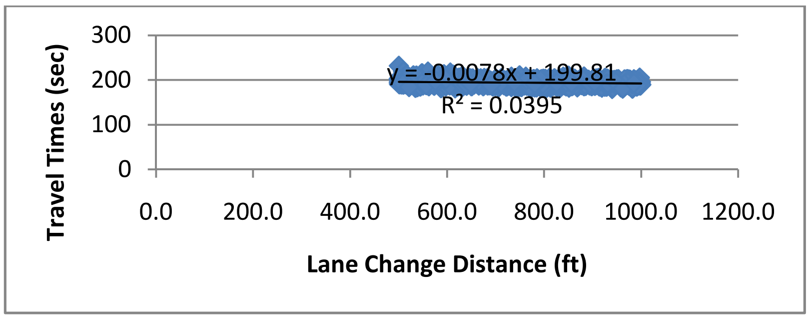
Figure 98(a-e): 75% Volume Scenario, Iteration #2, Parameter #18 Scatter Plots



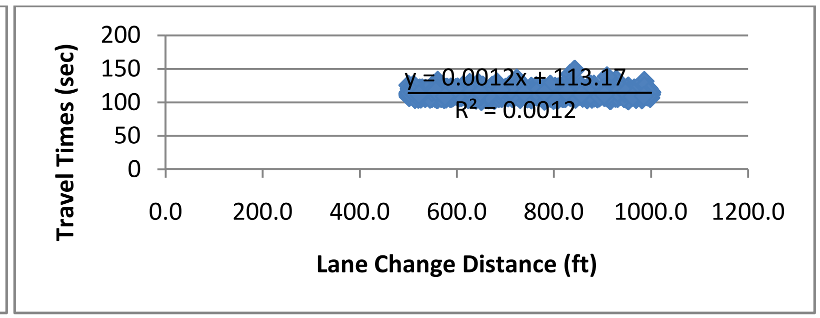
(a) Travel Time Segment #1



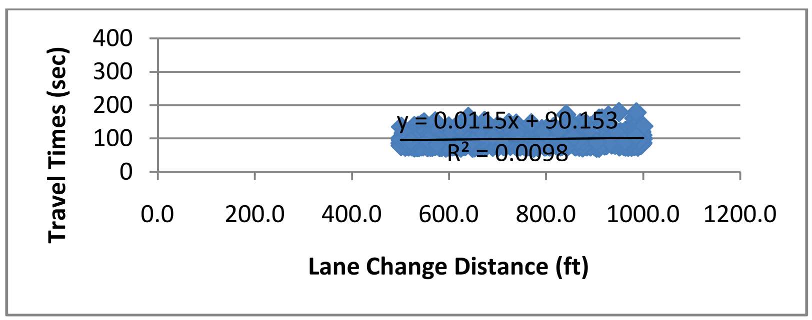
(b) Travel Time Segment #2



(c) Travel Time Segment #3

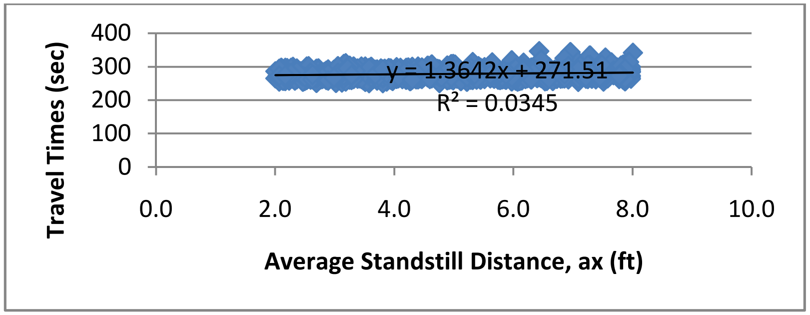


(d) Travel Time Segment #4

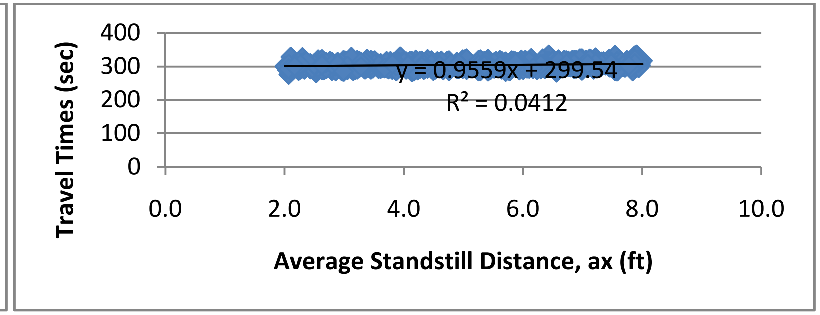


(e) Travel Time Segment #5

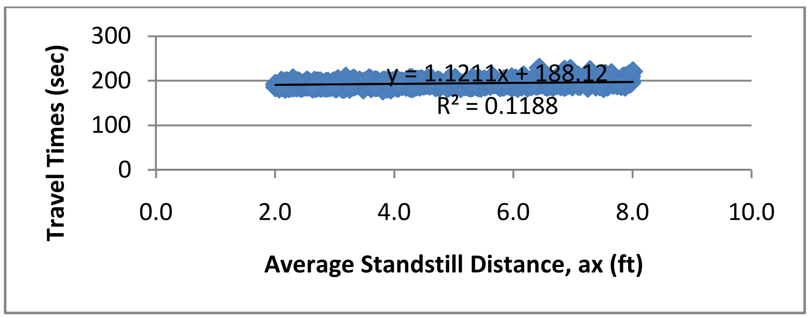
Figure 99(a-e): 75% Volume Scenario, Iteration #2, Parameter #22 Scatter Plots



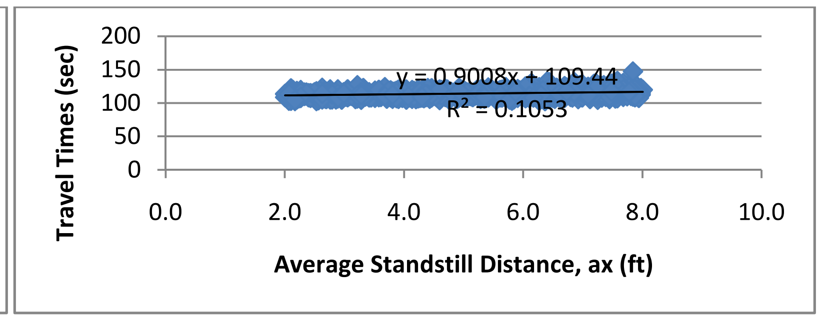
(a) Travel Time Segment #1



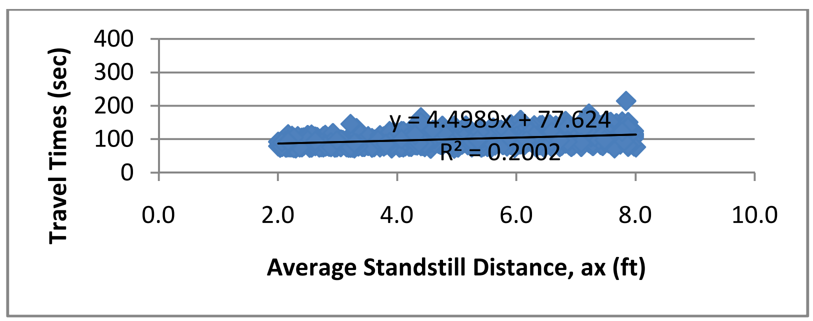
(b) Travel Time Segment #2



(c) Travel Time Segment #3

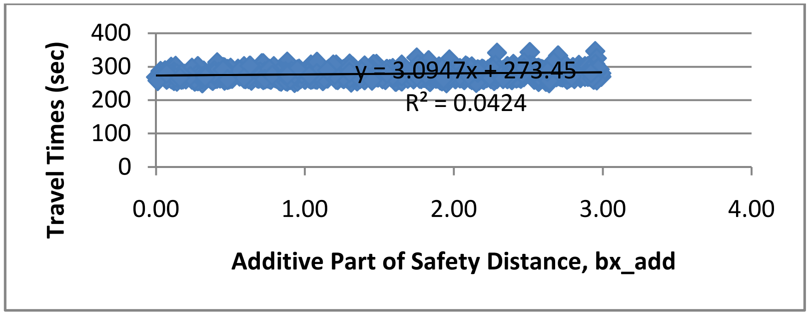


(d) Travel Time Segment #4

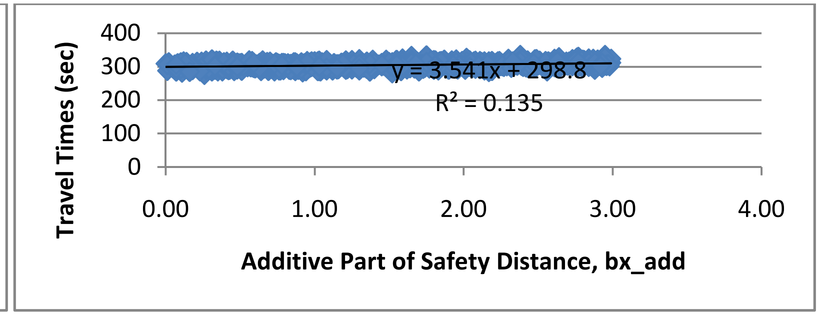


(e) Travel Time Segment #5

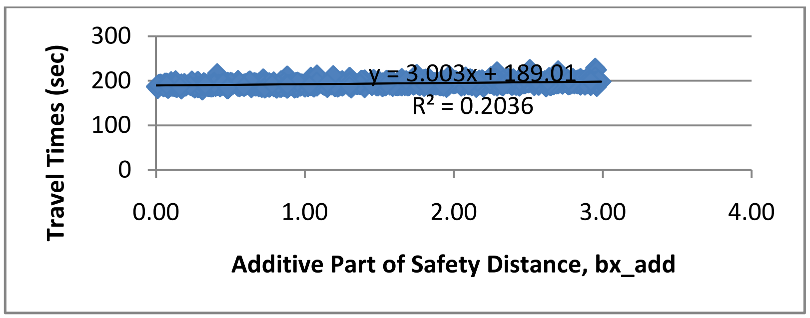
Figure 100(a-e): 75% Volume Scenario, Iteration #3, Parameter #5 Scatter Plots



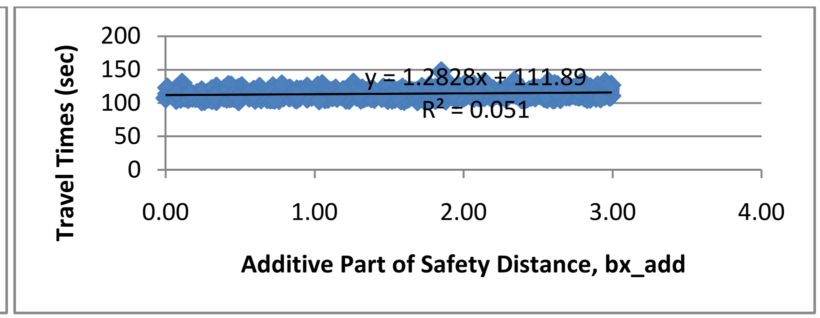
(a) Travel Time Segment #1



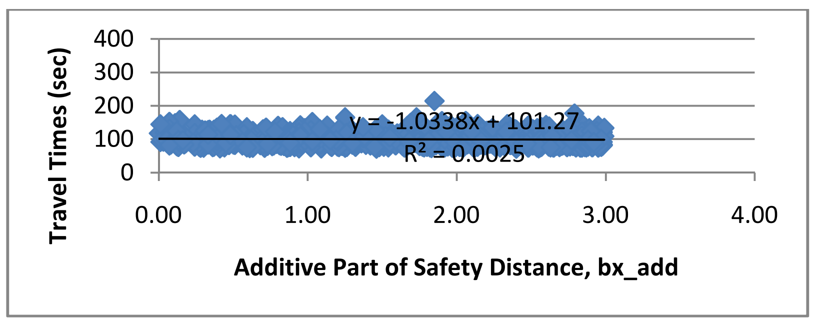
(b) Travel Time Segment #2



(c) Travel Time Segment #3

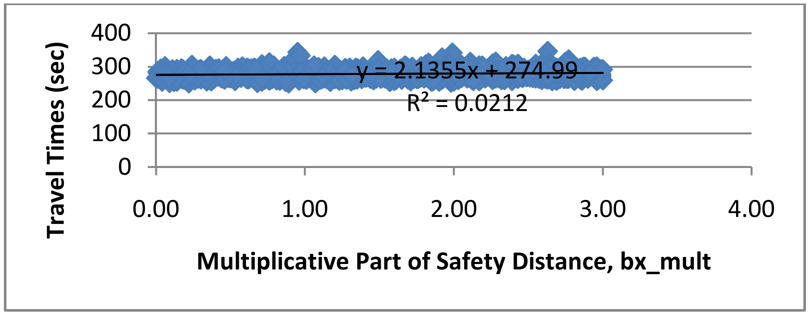


(d) Travel Time Segment #4

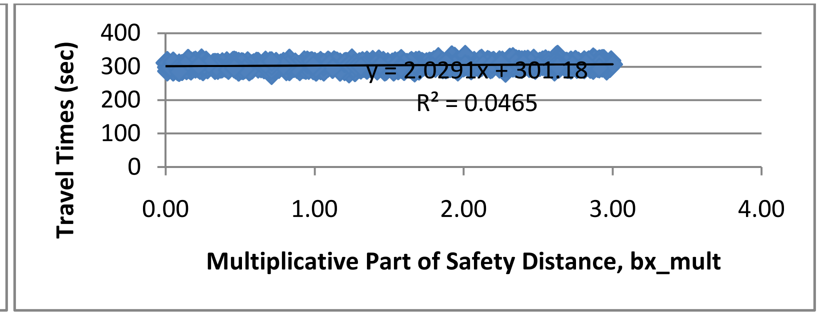


(e) Travel Time Segment #5

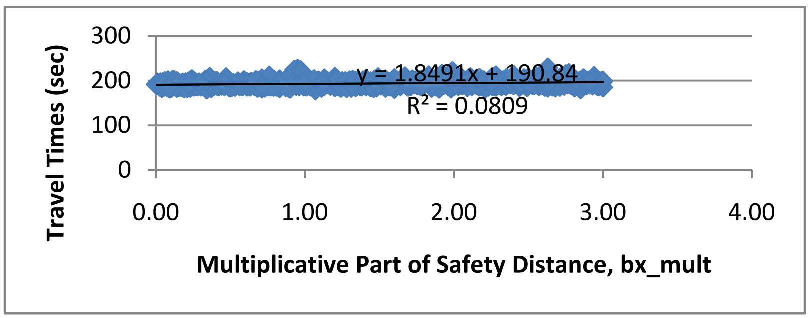
Figure 101(a-e): 75% Volume Scenario, Iteration #3, Parameter #6 Scatter Plots



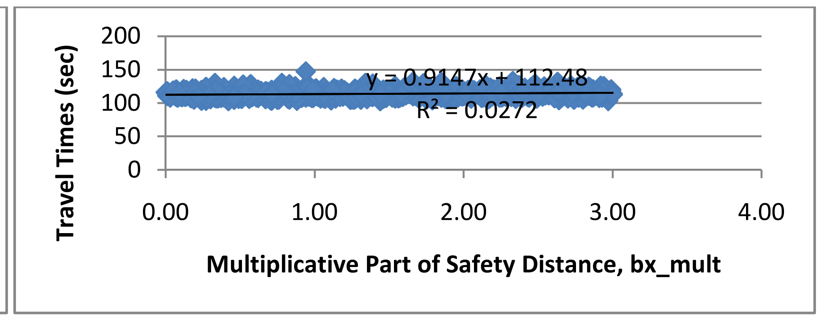
(a) Travel Time Segment #1



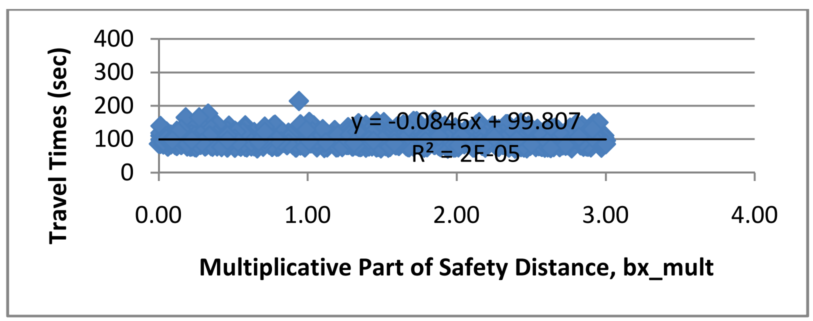
(b) Travel Time Segment #2



(c) Travel Time Segment #3

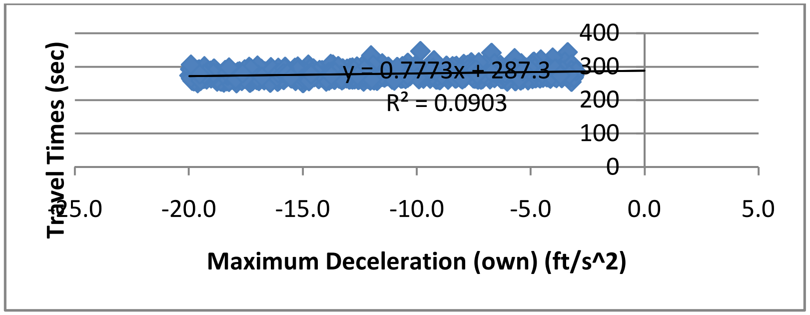


(d) Travel Time Segment #4

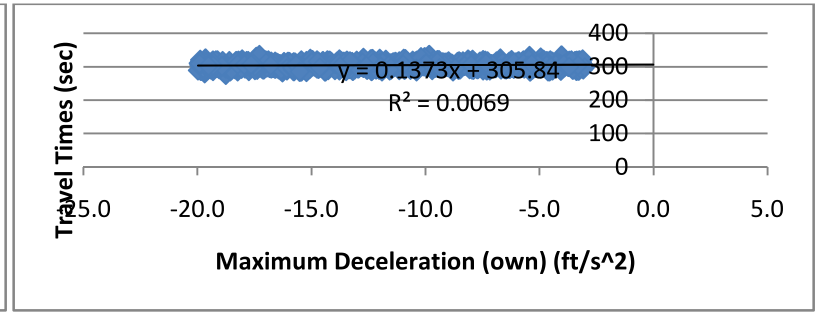


(e) Travel Time Segment #5

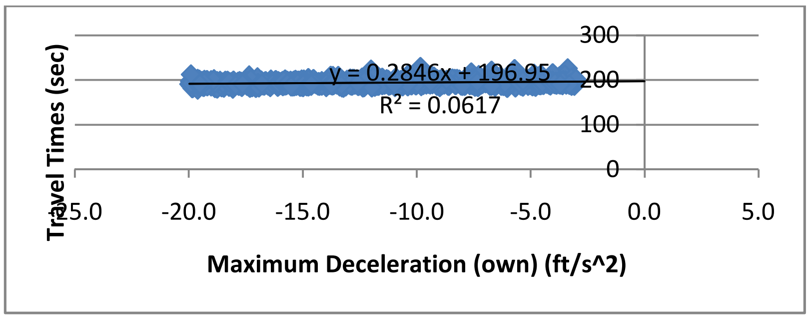
Figure 102(a-e): 75% Volume Scenario, Iteration #3, Parameter #7 Scatter Plots



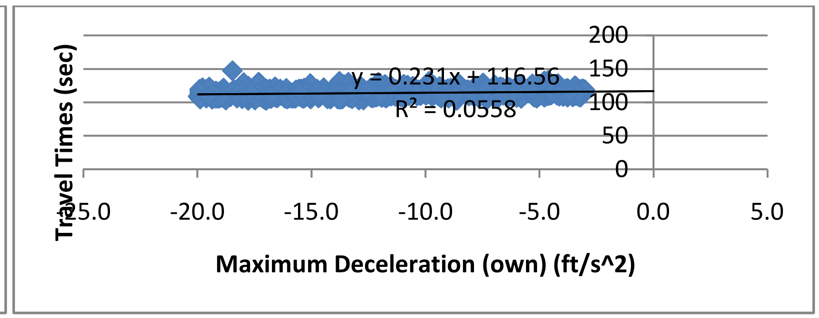
(a) Travel Time Segment #1



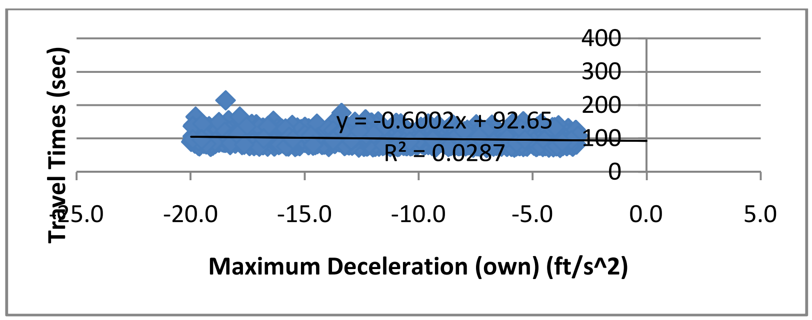
(b) Travel Time Segment #2



(c) Travel Time Segment #3

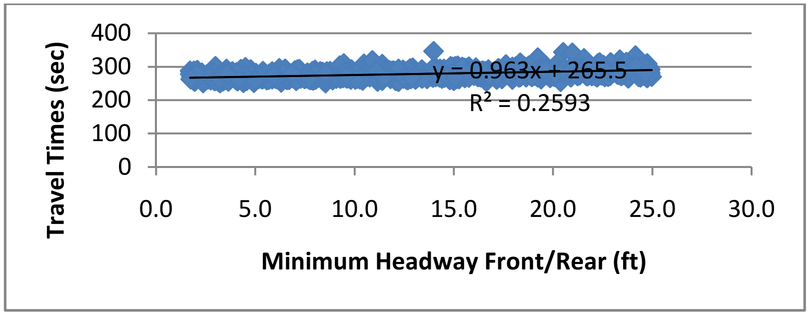


(d) Travel Time Segment #4

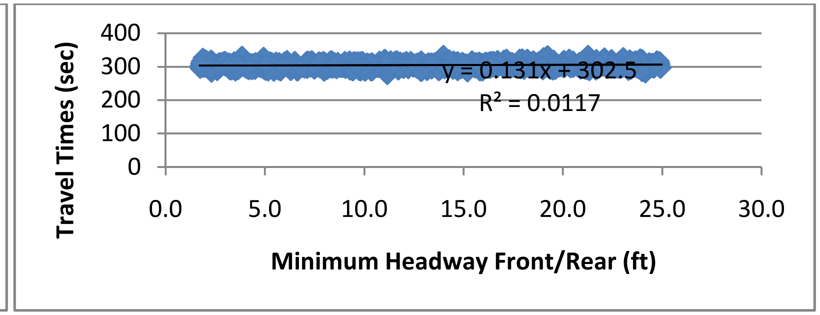


(e) Travel Time Segment #5

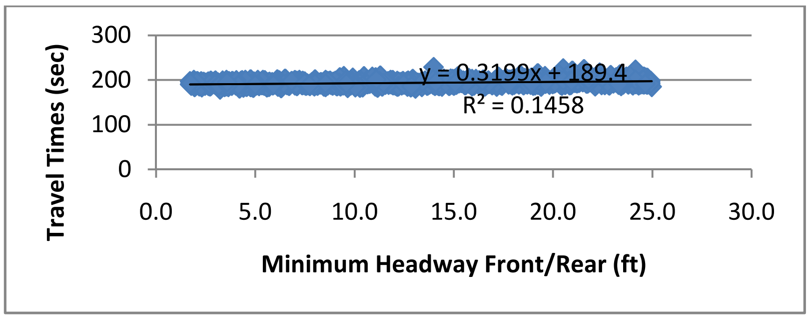
Figure 103(a-e): 75% Volume Scenario, Iteration #3, Parameter #8 Scatter Plots



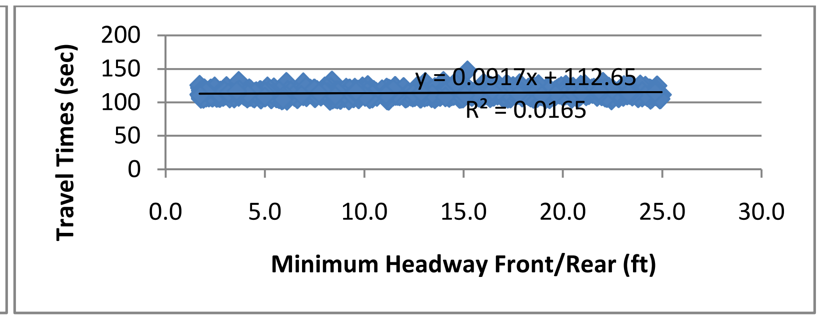
(a) Travel Time Segment #1



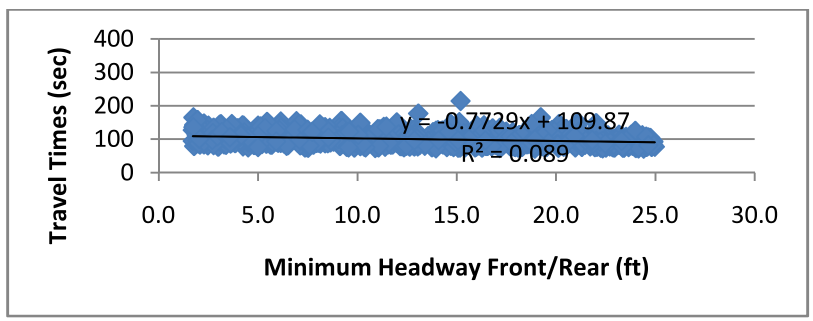
(b) Travel Time Segment #2



(c) Travel Time Segment #3

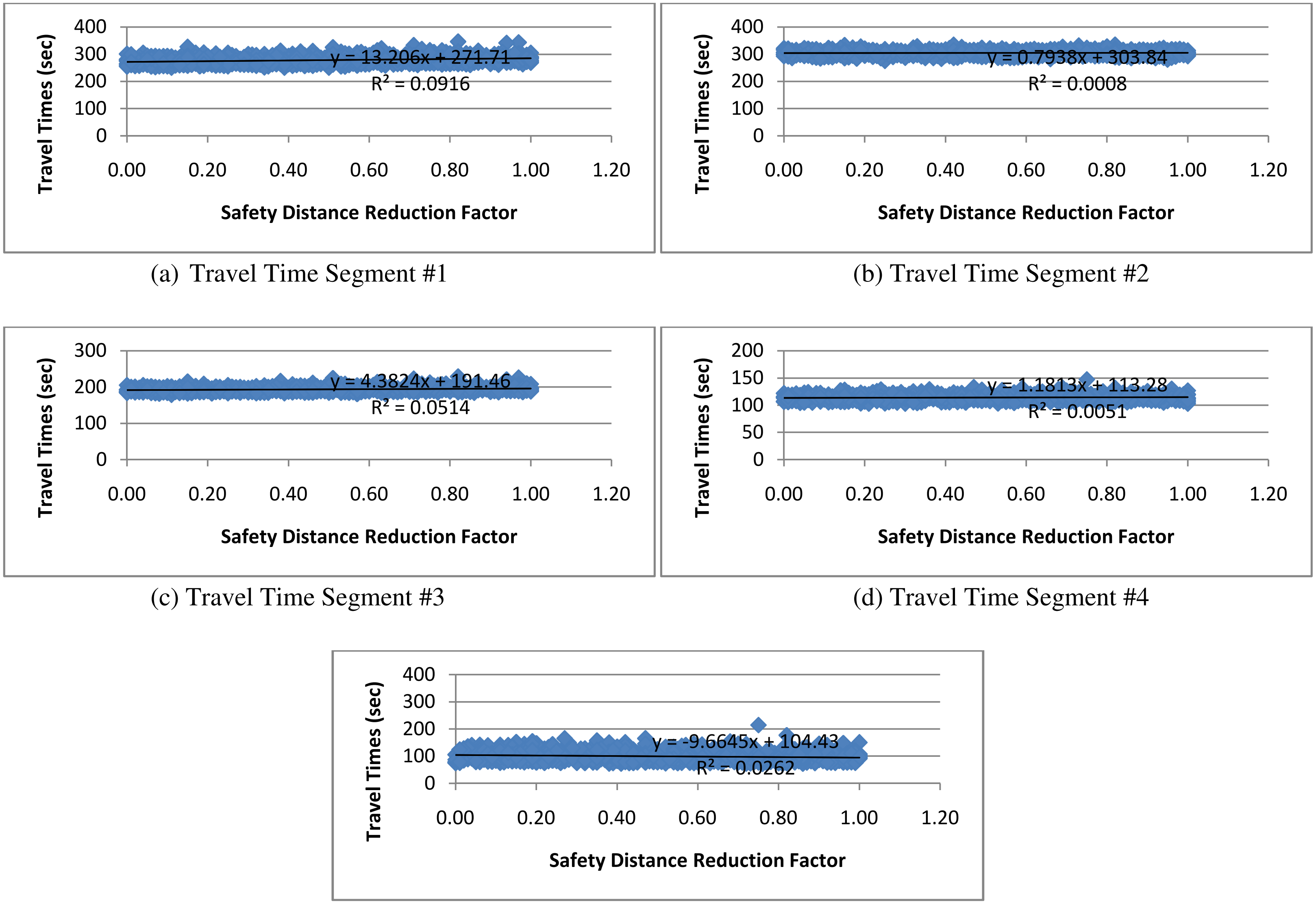


(d) Travel Time Segment #4



(e) Travel Time Segment #5

Figure 104(a-e): 75% Volume Scenario, Iteration #3, Parameter #15 Scatter Plots

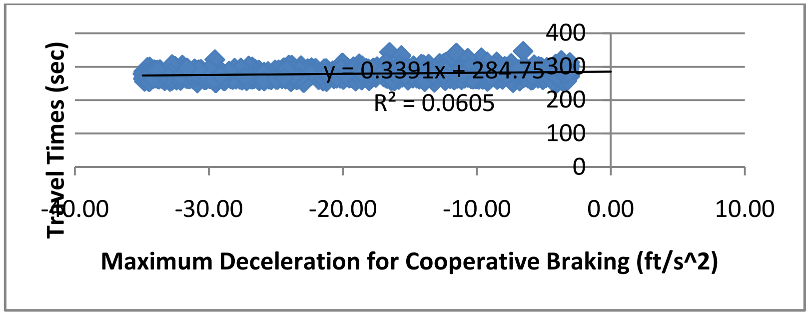


(a) Travel Time Segment #1 (b) Travel Time Segment #2

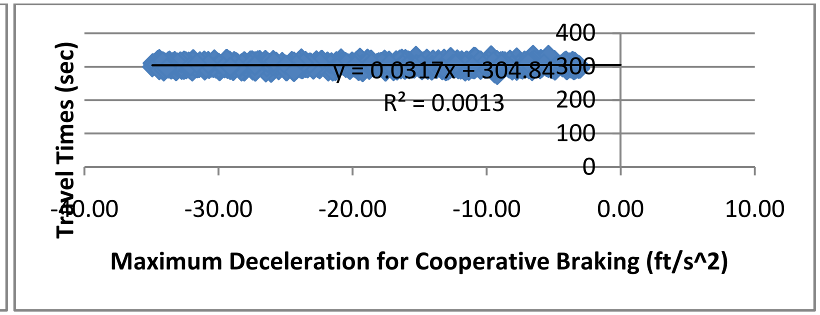
(c) Travel Time Segment #3 (d) Travel Time Segment #4

(e) Travel Time Segment #5

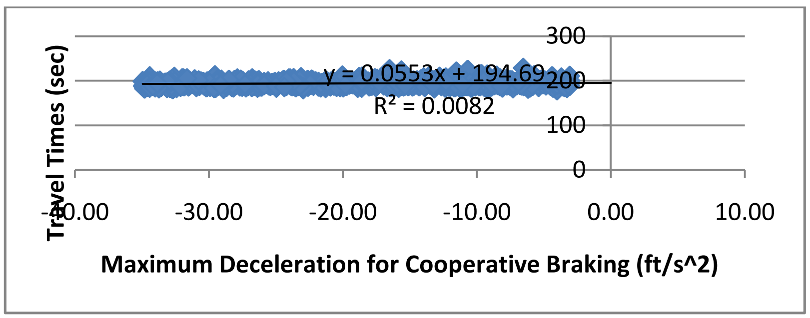
Figure 105(a-e): 75% Volume Scenario, Iteration #3, Parameter #16 Scatter Plots



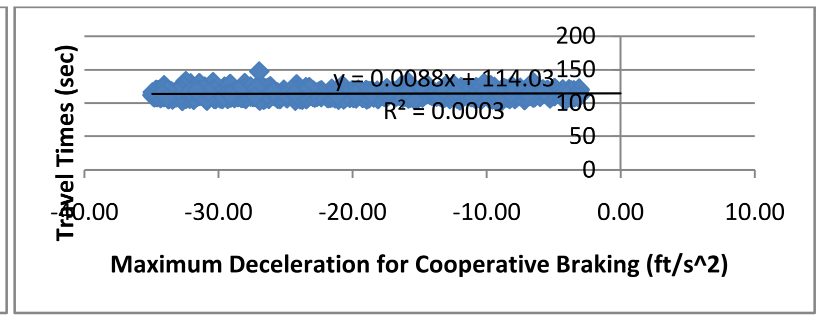
(a) Travel Time Segment #1



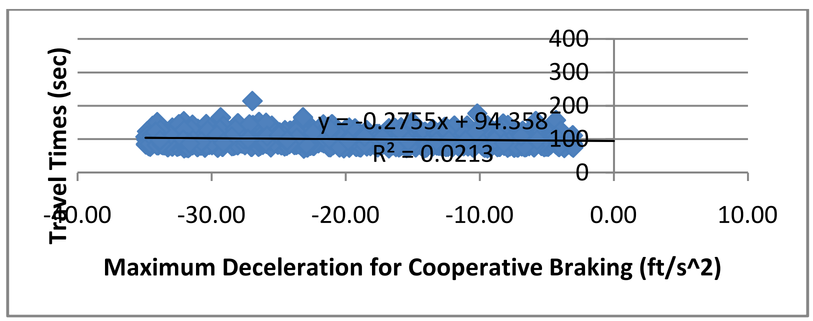
(b) Travel Time Segment #2



(c) Travel Time Segment #3

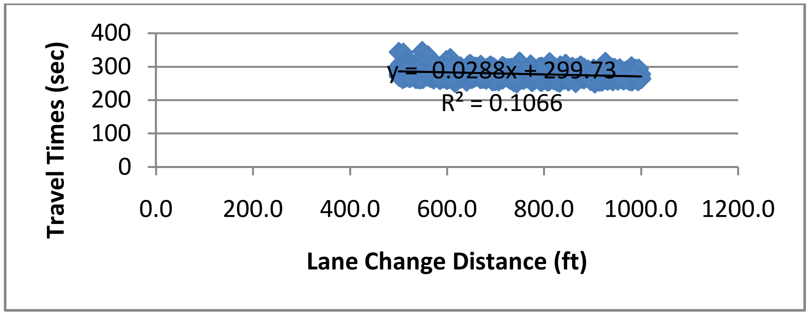


(d) Travel Time Segment #4

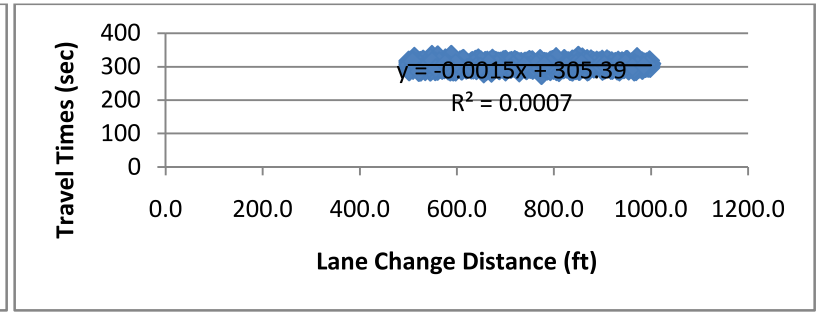


(e) Travel Time Segment #5

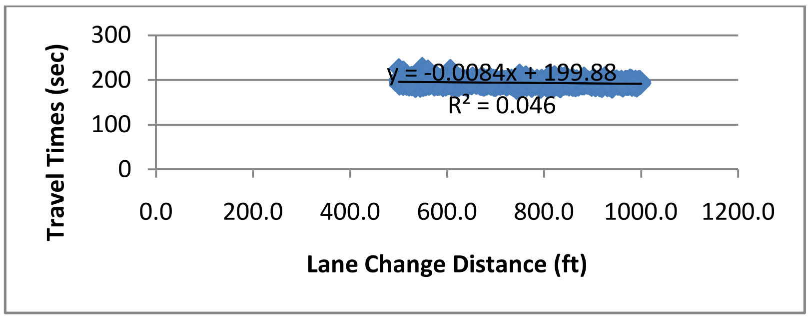
Figure 106(a-e): 75% Volume Scenario, Iteration #3, Parameter #17 Scatter Plots



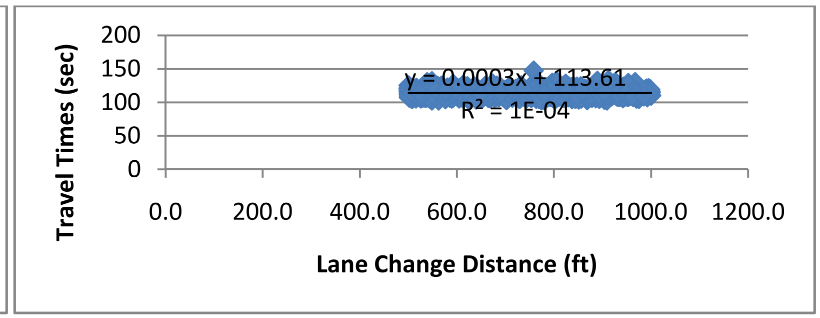
(a) Travel Time Segment #1



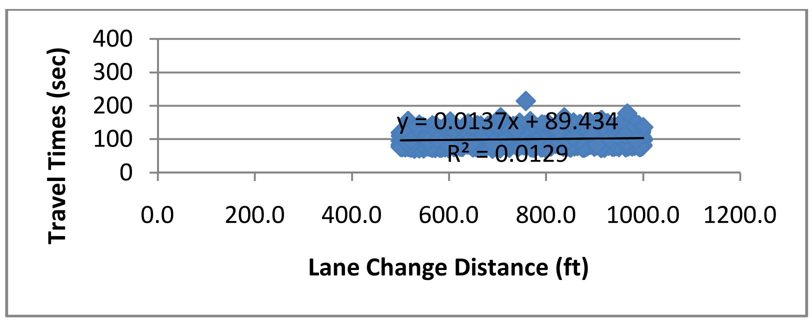
(b) Travel Time Segment #2



(c) Travel Time Segment #2



(d) Travel Time Segment #4



(e) Travel Time Segment #5

Figure 107(a-e): 75% Volume Scenario, Iteration #3, Parameter #22 Scatter Plots

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